BRINGING THE BREADWINNER BACK IN: RELATIVE WAGES AND DISEASES OF DESPAIR

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Abstract

The United States has recently witnessed a dramatic uptick in the morbidity of its White, working-class citizens. Economists have explained much of this uptick by noting the recent rise in "diseases of despair," such as alcoholism, within this population. However, they have often failed to explain why these diseases are much more prevalent among men than among women. In this paper, I advance a novel explanation for the recent increase in morbidity among White, working-class U.S. men. Drawing on research that indicates that heterosexual couples exhibit a strong aversion to situations in which wives outearn their husbands, I ask whether economic conditions that have led many men to lose their status as primary breadwinner have contributed to their declining health. Examining the impact of changes in men's breadwinner status on changes in their health outcomes, I observe that men who lose breadwinner status are 1.5 times more likely to report declines in health. However, men who are not breadwinners are also less likely to become obese and more likely to stop binge drinking. Changes in relative incomes within couples may indeed assist in explaining morbidity among men, though the direction of effects may be unexpected.

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1 Introduction

The past two decades have witnessed a remarkable, and troubling, surge in the mortality and morbidity of the U.S. White working class. Between 1999 and 2013, the mortality of multiple subgroups of White individuals in the United States, including those at midlife and those with a high school degree or less, increased dramatically, in significant part due to climbing deaths resulting from drug overdoses, suicide, and alcohol-related diseases (Case and Deaton, 2015). Famously termed "deaths of despair," these troubling deaths have inspired a frenzy of research that seeks to understand the determinants of recent declines in well-being among White Americans. The prevailing explanation for this rise in mortality suggests that deteriorating job opportunities have left White, working-class adults with few prospects, rendering them vulnerable to "diseases of despair," such as alcoholism and substance use disorders (Case and Deaton, 2017). However, this theory fails to account for gendered differences in the recent evolution of mortality and morbidity in the United States. Despair is not distributed evenly between men and women, and the causes of these crises, too, may differ by gender.

In this paper, I advance a novel explanation for the recent increase in so-called "diseases of despair" among White, working-class individuals in the United States. Drawing on research that suggests that heterosexual couples exhibit a strong aversion to situations in which wives outearn their husbands, I ask whether economic conditions that have led some White men to lose their status as the primary breadwinners within their families may have contributed to their unusually sharp uptick in diseases of despair (Bertrand et al., 2015; Basbug and Sharone, 2017). Leveraging unemployment events as plausibly exogenous shocks to breadwinner status, I test whether unemployment-induced losses of breadwinner status among men have contributed to recent declines in their mental and physical health. In addition, I examine the health impacts of changes in breadwinner status that are unrelated to employment status. My research centers on men, regardless of race, but I control for the health impacts of race and compare results between men and women. My analyses leverage data on heterosexual couples from the Panel Study of Income Dynamics to assess whether longitudinal and cross-sectional variation in intracouple income distributions impacts the mental and physical health of men. Together, these analyses bring gender back in to the study of the causes of the rise in diseases of despair among White, U.S. men, examining whether gender norms may have contributed to this uptick.

My results reveal that breadwinner status has varying effects on the health of men. Men who lose their breadwinner status are 1.5 times more likely to indicate that their health had worsened over time compared to those men who do not experience breadwinner status losses. Yet *not* being the breadwinner also renders men less likely to become obese and less likely to begin binge drinking over time, suggesting that although men who are not primary earners may experience relatively poor holistic health and well-being, they may also see improvements in certain aspects of their health. Together, these results suggest that relative incomes may indeed assist in explaining the recent evolution of health among U.S. men. Further research can clarify the extent to which changes in breadwinner status can explain variation in male morbidity on a national scale.

This analysis makes several contributions to the economics literature. First, it introduces a novel, distinctly gendered causal channel for understanding gender disparities in the recent rise in diseases of despair. Existing research on the causes of the uptick in morbidity among White Americans typically seeks to describe how singular economic or social shocks, such as declines in manufacturing employment, have affected both men and women. If these accounts locate gender disparities in the prevalence of diseases of despair, they attribute them to the differences in the degree to which a particular shock has affected men and women, such as by observing that men are more susceptible to manufacturing job loss given their disproportionate employment in the manufacturing industry (Pierce and Schott, 2016). Yet in assuming that a singular causal channel can explain why both men and women develop diseases of despair, these "gender-blind" explanations potentially obscure alternative variables that may interact with gender to affect men and women in qualitatively different ways. Men may experience heightened risk of developing diseases of despair not merely because they are impacted to a given shock to a different degree than women, but because they experience adverse health effects related an omitted social or economic factor, such as gender norms, that interacts with the shock to produce distinctly gendered effects. In introducing one such potential omitted factor here, I provide an initial exploration of the role of distinctly gendered causal channels in informing gender disparities in diseases of despair.

Second, this analysis provides the first quantitative exploration of the impacts of relative incomes within couples on physical and mental health. Classic qualitative research suggests that men experience the loss of their status as primary breadwinner as deeply disturbing, exhibiting "deep frustration" in light of their new failure to fulfill the traditional male provider role (Komarovsky, 1940, 74). In labor economics, a growing empirical literature confirms that couples exhibit an aversion to situations in which wives outearn their husbands. Married couples in which wives are primary breadwinners are more likely to divorce, and partners report decreased marital satisfaction (Bertrand et al., 2015; Folke and Rickne, 2020). Notably, this research has not examined whether these results vary by income or education (Bertrand et al., 2015; Folke and Rickne, 2020). These results suggest that gender norms surrounding relative incomes may affect couples emotionally, leading partners to exhibit marital discord and potentially to experience greater stress. Men who fail to fulfill societal gender norms may become especially despondent. However, no study has yet examined whether this emotional strife translates to adverse mental or physical health outcomes. In examining the impact of breadwinner status on the health outcomes of U.S. men, I open a new avenue for research on the causes of gender disparities in health.

This paper is organized as follows. Section 2 contextualizes my research question by providing an overview of the recent literature on diseases of despair and relative incomes. Section 3 describes the economic theory that motivates my empirical research. Section 4 presents my data, and section 5 outlines my empirical strategy. Section 6 presents my main results. Section 7 concludes.

2 Background

The mortality and morbidity of White Americans has increased substantially over the past two decades. Rises in the prevalence of "deaths of despair," a term that refers to deaths that result from drug and alcohol poisonings, suicide, and liver diseases and cirrhosis, and "diseases of despair," including substance use disorders and alcohol-related diseases, appear to account for much of the uptick in mortality and morbidity (Case and Deaton, 2017). (Morbidity refers to chronic pain and other self-reported physical and mental health conditions.) Recently, mortality and morbidity associated with deaths and diseases of despair has been especially prominent among White men, as opposed to White women. Yet previous attempts to explain this gender disparity has been met with little success, rendering its causes an open question. My research seeks to provide a novel explanation for this disparity by integrating insights from scholarship on deaths of despair and literature on relative incomes within couples. Below, I contextualize my research question by summarizing both of these literatures.

2.1 Deaths and Diseases of Despair

Research on deaths and diseases of despair has proliferated over the past decade. In 2015, a major research paper identified a marked rise in the mortality of White, non-Hispanic, middle-aged individuals living in the United States (Case and Deaton, 2015). Since then, scholars have sought to understand how "deaths of despair" may have contributed to this "mortality reversal." Here, I provide a brief overview of (1) the trends in U.S. White mortality and morbidity that spawned the growing literature on diseases of despair, (2) explanations for this growth in mortality and morbidity, and (3) racial and gender disparities in mortality and morbidity. This discussion provides a foundation for the introduction of my research question and approach.

Growth in Mortality and Morbidity Among White Americans

The mortality and morbidity of White U.S. residents has substantially increased over the past two decades, reversing earlier mortality declines. In a groundbreaking paper, Case and Deaton (2015) identified a marked rise in the all-cause mortality of White, non-Hispanic, middle-aged individuals in the United States over the past two decades. While the mortality of White, non-Hispanic U.S. residents between ages 45 and 54 fell by two percent annually during the 1980s and early 1990s, it instead *rose* by half a percent each year from 1999 to 2013. Further work has located prominent increases in mortality among White, non-Hispanic Americans within other age groups, particularly among those with a high school education or less (Case and Deaton, 2017). In general, these increases in mortality have been confined to White, non-Hispanic individuals, and they contrast with trends toward declining mortality in other rich countries. Black and Hispanic mortality in the United States has declined consistently over the past two decades, while White, non-Hispanic mortality has increased or declined only minimally (Case and Deaton, 2017). Rising mortality has been mirrored by climbing morbidity among U.S. Whites. The percentage of these individuals reporting "excellent" or "very good" health has declined across all educational levels and most age groups, while their reports of chronic pain and mental distress have increased (Case and Deaton, 2015). Together, these trends suggest a troubling, and unexpected, reversal of earlier declines in mortality and morbidity among White U.S. residents.

Seeking to explain this "mortality reversal," scholars have observed that the recent uptick in mortality among U.S. Whites can be accounted for in significant part by growth in "deaths of despair," or deaths to suicide, drug and alcohol poisoning, and chronic liver diseases and cirrhosis (Case and Deaton, 2017). For example, deaths of despair among U.S. White, non-Hispanic individuals ages 50 to 54 increased by 5.4 percent annually between 1999 and 2015, far exceeding growth in these deaths among Black and Hispanic U.S. residents and residents of other rich countries. Beyond those deaths typically included within the "deaths of despair" label, slowdowns in progress in reducing heart disease and cancer mortality among U.S. White individuals have also contributed to their rise in mortality (Case and Deaton, 2017). However, the uptick in deaths of despair has been sufficiently large that it has reversed declines in all-cause mortality that have resulted in part from progress against these diseases among certain groups of White Americans (Case and Deaton, 2017). Rises in "deaths of despair" among White Americans have been paralleled by increases in "diseases of despair," which may include depression, alcoholism, hypertension, and obesity, among other diseases. For example, White Americans reported increasing heavy alcohol use between 1997 and 2013 (Case and Deaton, 2015). These trends, and their unique prominence among White individuals in the United States, have presented a puzzle for researchers seeking to explain the recent evolution of public health in the United States.

Explaining the Crisis

The reasons for the uptick in "deaths of despair" and "diseases of despair" remain contested. On the one hand, a growing literature links rising morbidity and mortality among White Americans to adverse economic conditions. However, other scholarship suggests that morbidity and mortality are in fact procyclical, improving when conditions are poor.

First, a growing body of research in health economics and international economics locates a connection between declining economic conditions and mortality increases. For example, Case and Deaton (2017) situate recent increases in mortality and morbidity as the product of *cumulative disadvantage* faced by White Americans. They attribute the declining health of White Americans to a set of factors that have cumulatively degraded their sources of economic and social support, such as deteriorating job opportunities for individuals with low levels of education and declines in marriage and church attendance. In keeping with this framework, a number of scholars have linked the declining health of White Americans to manufacturing layoffs that have eroded their economic stability. For example, Pierce and Schott (2016) examine how a trade shock that disrupted U.S. manufacturing employment impacted the health of workers in affected areas. Counties with greater exposure to the trade shock exhibited higher rates of deaths to suicide, alcohol-related liver diseases, and accidental poisonings, a category which includes drug overdoses. Further research observes association between this manufacturing decline and male premature mortality, but locates no relationship between trade liberalization and opioid use (Autor et al., 2019; Ruhm, 2018; Janz, 2020). Trade liberalization may have contributed to the rise in deaths and diseases of despair, but it may not constitute the sole cause of the crisis.

On the other hand, macroeconomic declines have been linked to *improvements* in health. The basic premise of the cumulative disadvantage argument, that adverse economic conditions harm health, has been contested by scholars who argue that mortality and morbidity are in fact procyclical (Ruhm, 2016, 2000). For example, Ruhm (2016) observes that severe, national economic recessions reduce mortality, while localized economic crises do not consistently affect mortality. To explain growth in diseases of despair, Ruhm (2018) looks not to declining economic conditions, but to changes in the drug environment, arguing that shifts in the availability of drugs, including illicit opioids and opioid analgesics, account for the mortality uptick.

Integrating these two, conflicting lines of research to formulate a uniform hypothesis as to how economic shocks affect mortality and morbidity is difficult. However, it is possible that while health may improve in response to generalized declines in economic conditions, group-specific declines in economic conditions, such as local geographic declines and declines that disproportionately affect certain racial groups or people of certain genders, may harm health.

Racial and Gender Stratification

Diseases of despair are not distributed evenly by race or gender. However, relatively little research has examined these disparities in depth, and even less scholarship has sought to explain the causes behind racial and gender disparities in the prevalence of deaths and diseases of despair. Research that clarifies the reasons for these disparities may assist in illuminating the causes of broad-based growth in these diseases.

First, attention to rising mortality among U.S. Whites has often obscured the high absolute morbidity and mortality faced by Black and Hispanic communities. Researchers have consistently located greater increases in deaths and diseases of despair among White, non-Hispanic Americans relative to Black and Hispanic Americans (Case and Deaton, 2015, 2017). Yet absolute morbidity and mortality among Black and Hispanic Americans still largely eclipses that of U.S. Whites. For example, while mortality has risen sharply among middle-aged Whites, absolute mortality rates are still substantially higher among Black Americans at midlife than among Whites (Gennuso et al., 2019). Rather than leading Whites to experience greater mortality relative to other racial groups, increases in White mortality in the United States have effectively contributed toward closing racial gaps in mortality in which Whites previously had large advantages (Case and Deaton, 2017). Media and scholarly attention to research on White mortality increases has led scholars to suggest that these findings have "unexpectedly positioned working-class Whites as the new face of disadvantage, despite racial/ethnic minority groups in the United States having long histories of deprivation" (Brown and Tucker-Seeley, 2018, 124).

Further, while much scholarship suggests that diseases of despair have largely been confined to U.S. Whites, some very recent research suggests that racial gaps in the rates of increase of diseases and deaths of despair may be waning. While mortality rates decreased for most U.S. racial groups *except for* Whites and American Indians/Alaska Natives in certain age groups between 2007 and 2009-2012, one study finds that since 2009-2012, mortality has *increased* across most U.S. racial groups (Gennuso et al., 2019). Further, since 2015, all-drug poisoning death rates have hit new highs among Black Americans, suggesting that rises in these "deaths of despair" are increasingly tending away from being concentrated among Whites (Plunk et al., 2018). If rising despair was once a largely White problem in the United States, this may be becoming progressively less true.

Explanations for these racial gaps are thin. While Case and Deaton (2017)'s cumulative disadvantage hypothesis suggests that recent shifts in social and economic conditions have increasingly disadvantaged White people, Brown and Tucker-Seeley (2018) ask why the same changes in social and economic conditions have not also led to increases in mortality among Black and Hispanic Americans (p. 124). Deteriorating labor force conditions, growing financial insecurity, and low marriage rates have not been confined to Whites. Further, although Black Americans experience worse educational, income, wealth, and homeownership outcomes than Whites, they have seen mortality improvements (Brown and Tucker-Seeley, 2018). Given this lack of scholarly consensus regarding the causes of racial disparities in diseases of despair and the potentially growing prevalence of these diseases among non-White Americans, I explore the impact of changes in the relative incomes of partners on the health of all U.S. residents, rather than limiting my analyses to a single racial group.

Disparities in the prevalence of deaths and diseases of despair between men and women have received even less attention than racial disparities. Yet some research suggests that gender may play a distinct role in informing health outcomes. For example, drug, alcohol, and suicide mortality among White, non-Hispanic U.S. men ages 50 to 54 far exceeded that of women between 1992 and 2018 (Case, 2020). Further, although women are more likely to use opioids, opioid misuse is largely concentrated among men, and men have been more likely to meet clinical criteria for opioid dependence (Serdarevic et al., 2017; Silver and Hur, 2020). The marked increases in deaths of despair among U.S. White men at midlife are notable in that they contrast with overall mortality trends; in general, middle-aged U.S. White women have experienced larger relative increases in all-cause mortality (Case and Deaton, 2017). The prevailing explanations for these gender gaps in diseases and deaths of despair are incomplete. Pierce and Schott (2016) seek to explain these gender disparities by observing that White males tend to be disproportionately employed in manufacturing, an industry that experienced exceptional recent job losses and for which job losses have been tied to deaths of despair in the literature. However, Cutler (2017) contends that the effects of this shock on such deaths are relatively modest and unable to explain the magnitude of the uptick in deaths of despair. The question of which factors may have contributed to gender disparities in deaths and diseases of despair remains open.

2.2 Relative Incomes

Recent literature in labor economics on the relationship between the relative wages of men and women and their life outcomes provides one potential explanation for rise in diseases of despair among White, U.S. men. Existing research on relative wages strongly suggests that intrahousehold wage distributions may affect the emotional health of partners, potentially leading them to experience distress similar to that which some authors suggest has contributed to the recent uptick in morbidity and mortality among White Americans (Case and Deaton, 2017). Integrating these two scholarly traditions may explain gender disparities in the growth in diseases of despair in the United States.

First, a growing literature in labor economics suggests that distributions of income between partners in married couples impact their marital and life outcomes. Frequently, this research observes that partnerships in which husbands are the primary breadwinners experience more favorable outcomes than couples in which wives outearn their husbands. Bertrand et al. (2015) demonstrates that couples in which women outearn their husbands experience adverse marital outcomes. Examining survey data from between 1988 and 2002, the authors observe that whether or not a couple has a female breadwinner predicts whether or not individuals will indicate that they are in a happy marriage, that they are having marital problems, and that they have discussed separating, with female-breadwinner couples experiencing worse outcomes. Couples with female breadwinners are 6 percent more likely to divorce. The authors conceptualize these marital issues as responses to the social prescription that "a man should earn more than his wife," a gender norm that induces an aversion to situations in which women earn more than their husbands.

Further empirical research has confirmed an aversion to female breadwinning among married couples. Married couples in which women are promoted to top jobs and become more likely to outearn their husbands are more likely to divorce in Sweden, though couples do not become more likely to divorce when men achieve promotions (Folke and Rickne, 2020). Relatedly, respondents to a U.S. survey experiment exhibited a consistent preference for male breadwinning, regardless of their gender, age, or race (Tinsley et al., 2015). Notably, at least one study suggests that the male breadwinner norm may be fading as society trends toward greater gender equality. Schwartz and Gonalons-Pons (2016) find that although wives' relative earnings were positively associated with the risk of divorce for U.S. couples married in the late 1960s and 1970s, this effect faded for couples married in the 1990s. The authors observe that a decline in the salience of relative incomes is especially prevalent among middle-earning husbands and individuals without college degrees, hypothesizing that economic adversity may have incentivized these households to support greater flexibility in the breadwinner role.

Recent quantitative research on relative wages follows a longstanding ethnographic tradition that has consistently located an aversion to female breadwinning among U.S. couples. In a classic ethnography of men who became unemployed during the Great Depression, Komarovsky (1940) observed that men who lost their role as provider to unemployment experienced "deep humiliation" in light of their inability to fulfill "the very touchstone of [their] manhood—the role of family provider" (p. 74). More recent research indicates that even as gender egalitarianism in employment has increased, the male breadwinner norm has proven "sticky" or resilient. In an ethnography of U.S. working families first published in 1989, Hochshild and Machung (2012) describe how one wife, "Nina Tanagawa," quit the job that led her to earn more than her husband, "Peter," to relieve Peter's shame regarding his status as non-breadwinner. In a more recent ethnography, Basbug and Sharone (2017) observe that married men, but not married women, experience marital tensions related to the provider role. Men may feel an emotional attachment to the breadwinner role, experiencing loss of this role as painful.

2.3 Bringing the Breadwinner Back In

By integrating insights from the literature on both diseases of despair and relative wages, this study proposes a novel explanation for gender disparities in diseases of despair. Recent literature in economics suggests that a range of social and economic factors have contributed to increases in the prevalence of diseases of despair among U.S. men. Yet this research has failed to account for the full extent of disparities in disease prevalence between men and women, suggesting that omitted variables may have also contributed to gender disparities in morbidity. The literature on relative incomes identifies one such variable. Further, men who lose their breadwinner status as a result of unemployment may experience a "double blow" to their health, experiencing adverse mental health effects both as a result of their job loss and in light of their new inability to fulfill gender norms that privilege men who are primary earners. Economic conditions that have led men to lose their breadwinner status may have contributed to declines in health among White men in the United States.

In this study, I "bring the breadwinner back in" to scholarship on diseases of despair by examining whether relative incomes may have contributed to declines in the health of U.S. men. My analyses test the hypothesis that losses of breadwinner status lead men to experience adverse health outcomes, including "diseases of despair," such as mental illness, binge drinking, obesity, and hypertension. By providing a preliminary test of the proposition that breadwinner status loss may contribute to adverse health outcomes among U.S. men, my research paves the way for further analyses of the extent to which gender norms can assist in explaining national upticks in the prevalence of diseases of despair among White, working-class U.S. men.

3 Theoretical Background

Economic theory and empirical research suggests that health responds not only to breadwinner status, but also to an assortment of additional economic variables, such as income and unemployment. This section provides (1) an overview of these variables and their effects on health and (2) a theoretical model that illuminates the ways in which these variables may interact with breadwinner status to inform health.

3.1 Economic Variables and Health

Existing research has firmly established relationships between unemployment, income, and demographic variables and health. Research that seeks to isolate the impact of breadwinner status on health must take into account these effects, particularly if interactions between breadwinner status and these variables may affect health. Here, I briefly summarize previous research on the health effects of unemployment, income, and a set of demographic variables.

Unemployment

Empirical economics research documents adverse impacts of unemployment on a range of mental and physical health outcomes and behaviors, including (1) mental health and subjective well-being, (2) hypertension and cardiovascular diseases, (3) obesity, and (4) alcohol use, among others. These health impacts last for a significant period of time after individuals initially lose their jobs, a phenomenon that researchers have described as the "scarring" effects of unemployment.

First, unemployment has frequently been linked to declines in mental health, happiness, and subjective well-being. Unemployed individuals have poorer mental health, life satisfaction, and marital satisfaction than their employed counterparts (McKee-Ryan et al., 2005). Notably, employed individuals may not constitute an adequate control group for unemployed individuals, as negative experiences in early childhood may affect both one's likelihood of job loss and of developing mental health problems in adulthood (Caspi et al., 1998; Merrick et al., 2017; Young, 2012). Yet panel research that assesses how mental health changes as individuals transition into and out of unemployment has also frequently observed inverse relationships between unemployment and mental health (Murphy and Athanasou, 1999). At least two recent studies have examined the impact of unemployment on mental health using U.S. panel data. Dooley et al. (2000) observe that individuals who become unemployed are more likely to develop depression, even when controlling for prior depression. Using Panel Study of Income Dynamics data, Young (2012) finds that individuals who transition from employment to unemployment experience significant declines in mental health. This research establishes a clear linkage between job loss and declines in mental health.

The effects of unemployment on mental health are *distinct* from the effects of income losses on mental health. Even when controlling for changes in in family income, individuals who become unemployed experience declines in well-being (Young, 2012). Individuals who experience job loss may internalize social stigmas surrounding unemployment and come to believe that they are "unworthy, incomplete, and inferior" (Jahoda et al., 2009). Employers discriminate against individuals who have been unemployed in the hiring process, believing these individuals to be less competent and hirable, and individuals who are conscious of these stigmas surrounding unemployment suffer from reduced well-being (Ho et al., 2011; Krug et al., 2019). Unemployment may affect mental health and subjective well-being for reasons that extend beyond the immediate effects of income losses on health.

Second, researchers have frequently hypothesized that unemployment increases risk of cardiovascular problems, typically invoking one of three potential causal mechanisms (Weber and Lehnert, 1997). Distress resulting from unemployment may contribute to biochemical and physiological changes that increase the risk of developing cardiovascular diseases; unemployment may lead to lifestyle changes, such as increased cigarette use, that contribute to cardiovascular issues; and financial problems associated with unemployment may induce psychosomatic symptoms (Weber and Lehnert, 1997). Recent research has bolstered these theoretical accounts by identifying robust, inverse correlations between unemployment and cardiovascular health. In a sample of Californian men, job insecurity and unemployment predicted hypertension even when controlling for potential moderating variables such as body mass index and physical activity, though associations were weaker for women (Levenstein et al., 2001). The association between unemployment and risk of acute myocardial infarction persists even after controlling for socioeconomic, clinical, and behavioral risk factors (Dupre et al., 2012). Unemployment may adversely affect cardiovascular health.

Third, existing research has identified linkages between unemployment and shifts in body weight. In general, there exists a split between the macro and micro literatures on unemployment and body weight: macro-level studies suggest that weight declines during recessions, but at the micro level, research indicates that individuals tend to gain weight when they become unemployed (Ruhm, 2000, 2005; Jónsdóttir and Ásgeirsdóttir, 2014). However, the direction of weight change may not serve as a useful indicator of "health," given that both abnormal weight loss and weight gain may indicate declining health. Individuals who become unemployed typically take up poorer quality diets, which may result in either weight gain or weight loss (Roelfs et al., 2011). Importantly, individuals who gain weight during unemployment may be at increased risk of suffering adverse consequences as a result of their weight change: overweight individuals, especially women, face employment discrimination (Roelfs et al., 2011; Wanberg, 2012). In the worst scenarios, this may lead to a cycle of unemployment in which individuals who gain weight as a result of their unemployment cannot obtain new employment, further compounding their health problems.

Finally, scholars have located mixed associations between unemployment and alcohol use. From a theoretical standpoint, the impact of unemployment on alcohol use is indeterminate. On the one hand, the distress associated with unemployment could lead individuals to increase their alcohol use as a "coping mechanism" (Roelfs et al., 2011; Popovici and French, 2013). However, individuals may also reduce their alcohol consumption when they become unemployed due to an "income effect," in which they spend less on alcohol given their decreased earnings (Compton et al., 2014). Most research on the topic suggests that alcohol use and binge drinking rises when individuals become unemployed, especially among men (Roelfs et al., 2011; Popovici and French, 2013; Compton et al., 2014). However, some work provides support for the alternative "income effect" hypothesis (Compton et al., 2014).

Using PSID data, Bolton and Rodriguez (2009) find that individuals who experience unemployment and do not receive unemployment benefits are more likely to report increases in alcohol use than continuously employed individuals.

Income

Income has also frequently been associated with health. In the United States, a vast literature on the social determinants of health locates negative associations between poverty and health outcomes (Braveman and Gottlieb, 2014; Galea et al., 2011). Disparities in access to health insurance coverage that restrict access to medical care exacerbate this relationship (Woolf et al., 2015). Poorer individuals are more likely to have depression, have hypertension, and be obese (Assari, 2018; Kaplan et al., 2010; Ogden et al., 2017). Among the health outcomes examined in this study, the only one for which income does *not* typically have an inverse relationship with health is alcohol use. Higher-income individuals are more likely to engage in hazardous use of alcohol, or to use alcohol while performing a dangerous activity, e.g., driving (Keyes and Hasin, 2008). In contrast, alcohol dependence is more common among individuals of low socio-economic status (Keyes and Hasin, 2008). Notably, factors such as level of education and race may complicate the income-health relationship (Chokshi, 2018). For example, having a higher household income has a protective effect against depression for White individuals living in the United States, but this is less true for Black individuals (Assari, 2018). The effects of income on health may be moderated by demographic variables.

Demographic Variables

Finally, demographic variables such as race, age, education, whether an adult has young children, and geography may impact health. An extensive discussion of the impacts of these variables on health is beyond the scope of this paper. However, population health research in the United States has established robust relationships between each of these variables and health (Deeks et al., 2009; Singh et al., 2017; Jarvis, 1996; Young, 2012). These variables may be correlated with breadwinner status as well as health: for example, older individuals may be more likely to take on traditional gender roles, with a male breadwinner and a wife who stays at home, and they may also be less healthy. Including these variables in an analysis of the impact of breadwinner status on health is important to avoiding omitted variable bias.

3.2 Theoretical Model

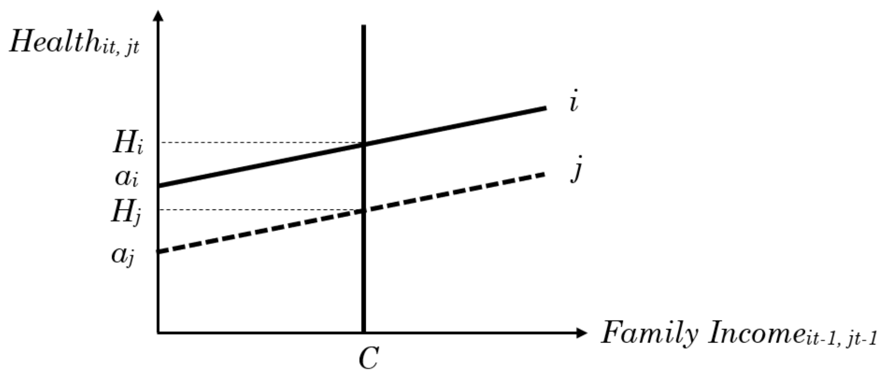
In the previous section, I demonstrated that a set of economic and demographic variables each have predicted relationships with health. How do these relationships affect the relationship between breadwinner status and health? Here, I develop a simple theoretical model to describe (1) the predicted impacts of these variables on health and (2) the impact of unemployment, breadwinner status, and the interaction of unemployment and breadwinner status on health.

Illustrating Health

The previous section described predicted relationships between a set of economic and demographic variables and health. Modeling the independent impacts of each of these variables on specific health outcomes is beyond the scope of this paper. However, I develop a simple illustrative model here to illuminate predicted relationships between a general measure of health and income, and I demonstrate how additional demographic variables might affect this model.

Figure 1 provides a simple representation of the relationship between health and the family income of an individual i, who is a member of a married, heterosexual partnership. In this model, I define family income as the combined labor incomes of both an individual and his or her partner, and I lag family income by one year to avoid potential reverse causality between income and health. Here, I predict that for a given individual i, health improves linearly as income increases over time. The intercept on the y-axis, a_i, comprises a vector of determinants of individual i's base level of health. As discussed in section 3.1, these determinants of health may include race, age, education, whether an adult has young children, and geography. This intercept also includes unobserved, time-invariant features of individuals that may render them more or less likely to be healthy: for example, their level of trust in healthcare institutions may affect how likely they are to seek preventative medical care services.

Figure 1: Relationship Between Health and Income



This figure contrasts the health of individual i with that of a second individual, individual j. Individual j is identical to individual i in every respect *except* that he or she has a different vector of determinants of his or her base level of health, represented by his or her unique intercept, a_j. For example, individual j may be of a different race or age than individual i, or he or she may possess different unobserved characteristics than individual i. At a given level of income C, individual j's level of health, H_j, is lower than individual i's level of health, H_i. Individual j possesses characteristics that render him or her less likely to have good health, regardless of income level: he or she may be older, less highly-educated, or otherwise different from individual i in a way that negatively impacts his or her health.

The objective of this paper, however, is not to understand the relationships between family income and health, but to understand the health impacts of breadwinner status. This illustration represents a *null hypothesis* situation, in which breadwinner status does *not* affect health. In the next section, I describe how unemployment and breadwinner status might alter the health of individual i in this illustration.

Modeling Breadwinner Status

In this section, I develop predictions as to how changes in breadwinner status, unemployment, and their interaction might affect health.

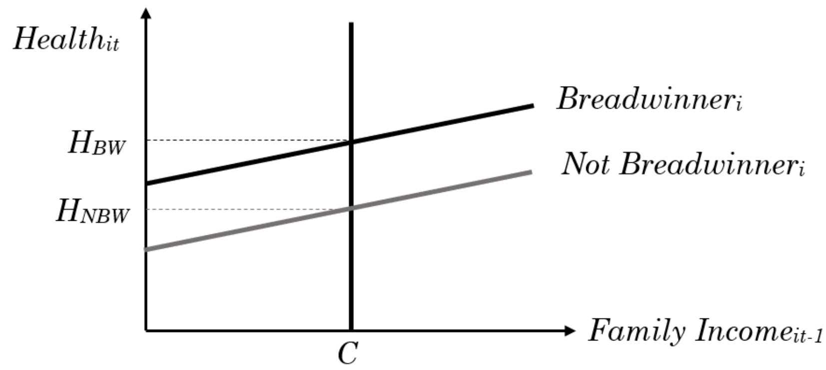
Breadwinner Status

First, I predict that lacking breadwinner status will adversely impact the health of men. The existing literature on breadwinner status does not explicitly address the potential health effects of breadwinner status. However, researchers have located evidence that men who are breadwinners may experience more marital satisfaction and less distress than men who are not breadwinners (Bertrand et al., 2015; Basbug and Sharone, 2017). I hypothesize that these declines in life satisfaction and increases in distress translate into declines in the health of men.

Figure 2 illustrates the predicted relationship between breadwinner status and men's health. Here, the health of an individual man who is breadwinner, $Breadwinner_i$, is compared to his health when he is not breadwinner. Beyond this difference in breadwinner status, the man is identical in all independent variables between both curves. The diagram indicates that men are healthier when they are breadwinners than when they are not. I predict that this effect is *independent* of family income: regardless of their family income, men may react negatively to not being breadwinner in light of social prescriptions surrounding breadwinner status. In the diagram, at a given level of family income, C, the level of health of breadwinning men, H_{BW}, eclipses that of non-breadwinning men, H_{NBW}, holding all else equal.

The relationship between breadwinner status and health may be less straightforward for women. If husbands experience health issues when they lack breadwinner status, wives may find it distressing to *possess* breadwinner status, if this leads their husbands to have problems. Women breadwinners may thus experience adverse health outcomes alongside their non-breadwinning partners. On the other hand, increases in relative wages may positively

Figure 2: Relationship Between Health and Breadwinner Status



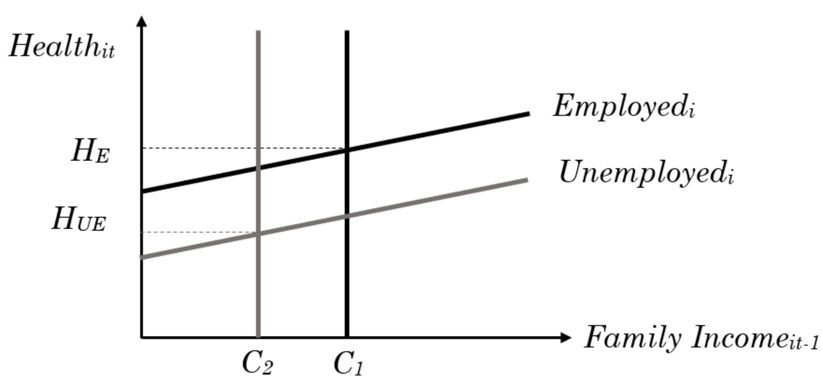
affect women's health, such as by enabling women to leave partnerships in which they experience domestic violence (Aizer, 2010). Given these conflicting mechanisms, a preliminary hypothesis is that breadwinner status has a smaller magnitude of effect on the health of women than it does for men.

Unemployment

Second, I am interested in the impact of unemployment on the health of partners. Unemployment likely affects health in at least two distinct ways. First, losses of income associated with unemployment may reduce health. Increases in income are typically health-promoting, while declines in income harm health (Braveman and Gottlieb, 2014; Galea et al., 2011; Assari, 2018; Kaplan et al., 2010; Ogden et al., 2017). Second, even beyond this "income effect," unemployment may adversely impact health and well-being by negatively impacting people's self-perceptions and senses of identity (Jahoda et al., 2009; Ho et al., 2011; Krug et al., 2019; Young, 2012). This "self-perception and identity" effect of unemployment may translate into worse mental health for individuals, and since mental health is typically strongly linked to physical health, it may lead to declines in physical health as well (Ohrnberger et al., 2017). Further, previous research suggests that these effects persist even when controlling for income losses (Young, 2012). Accordingly, I predict that unemployment adversely impacts health through two mechanisms.

Figure 3 illustrates both of these predicted effects of unemployment on health. First, I depict the income losses associated with unemployment as a transition from family income level C_1 to income level C_2. The adverse impact of unemployment on health via the "income effect" can be represented as a leftward movement along the $Employed_i$ curve from the point where this curve intersects with income curve C_1 to the point where it intersects with income curve C_2. The income losses associated with unemployment reduce individual i's health from H_E to the level of $Health_{it}$ at the point where the $Employed_i$ curve intersects income curve C_2. Second, the impacts of unemployment on health via the "self-perception and identity" effect are represented as a downward shift in the health curve, from $Employed_i$ to $Unemployed_i$. The "self-perception and identity" mechanism predicts that at any given level of income, an individual will experience worse health if he is unemployed than if he is employed. The final, combined effect of these two mechanisms is depicted as the total difference in health between an employed and unemployed individual, represented the difference between H_E and H_{UE}. These individuals are identical in all independent variables except employment status.

Figure 3: Relationship Between Health and Employment Status



The unemployment literature suggests that there may be a stronger link between unemployment and health for women than for men (Young, 2012). Since home-making is more common among women, women who do choose to enter the labor force may be a self-selected group for whom labor force attachment is particularly meaningful (Young, 2012). Accordingly, losing a job may be more distressing for women than for men. I predict that the "self-perception and identity" effect of unemployment described in this model will be stronger for women than for men, leading unemployment to impact the health of women more negatively.

Interaction of Unemployment and Breadwinner Status

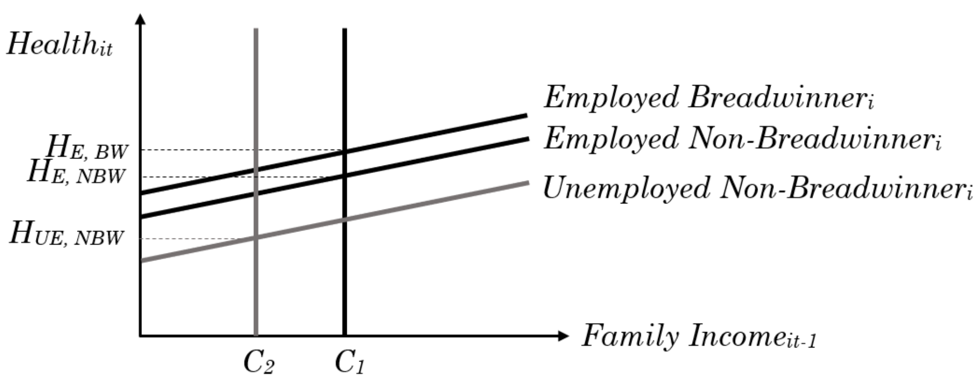
The impacts of breadwinner status on health may vary between individuals who *choose* not to be breadwinner and those who would prefer to be breadwinner but are unable to obtain an appropriate salary. For example, individuals who choose to give up breadwinner status so that they can take shorter hours to care for a child, work on a creative project, or for other reasons may not react as negatively to lacking breadwinner status as individuals who prefer to be breadwinner but lose breadwinner status when they experience an unexpected shock to their incomes.

In this paper, I predict that individuals who *choose* to lack breadwinner status will experience fewer adverse health effects than individuals who do *not* willingly give up breadwinner status. Since individuals typically do not willingly choose to become unemployed, I hypothesize that unemployed individuals are more likely to have lost breadwinner status unwillingly. Unemployment is often experienced as an unexpected and unwanted event, and individuals who become unemployed may experience earnings declines that lead them to lose breadwinner status. Accordingly, I predict that unemployed non-breadwinners, who may have lost their breadwinner status as a result of their unemployment, will have worse health outcomes than employed non-breadwinners. I hypothesize that this "lack of choice" effect is distinct from the effects of unemployment and breadwinner status outlined above. Further, I predict that this effect is independent of income: regardless of income, individuals who do not choose to lack breadwinner status may experience worse health outcomes than those who lack breadwinner status by choice.

Figure 4 illustrates the predicted effects of the interaction between unemployment and breadwinner status on health. The curves depicted in this diagram depict individuals who are identical in all independent variables except employment status and breadwinner status.

Here, being an unemployed non-breadwinner leads individuals to have health worse than that of both employed breadwinners and employed non-breadwinners. Relative to the employed non-breadwinner, the unemployed non-breadwinner experiences a decline in health related to the decline in family income associated with his or her unemployment, or an "income effect." This effect is depicted as the shift from the intersection of the *Employed Non-Breadwinner*$_i$ curve and the curve representing income level C_1 ($H_{E,NBW}$) to the intersection of the *Employed Non-Breadwinner*$_i$ curve and income curve C_2. However, this individual also experiences an adverse effect of unemployment on health that is independent from income: the combined effect of the "self-perception and identity" effect discussed previously and the "lack of choice" effect described above. This effect shifts the unemployed non-breadwinner's health curve downward, from *Employed Non-Breadwinner*$_i$ to *Unemployed Non-Breadwinner*$_i$. The total effect of being an unemployed non-breadwinner on the health of an individual i drops his or her level of health from $H_{E,BW}$ to $H_{UE,NBW}$. This model thus predicts that unemployed non-breadwinners will typically have worse health than employed non-breadwinners, regardless of income.

Figure 4: Interaction of Unemployment and Breadwinner Status



A discussion of the plausibility of the assumption that unemployment constitutes an unexpected shock to breadwinner status can be found in Data Appendix A.

4 Data

This study uses data from ten waves of the Panel Study of Income Dynamics (PSID). The longest-running longitudinal household survey in the world, the PSID provides detailed data on the labor force activity, health, and demographic characteristics of individuals and families in the United States. The PSID employs a genealogical sample design in which individuals are added to the study sample if they marry or are born into a previously sampled family. New individuals thus enter into my sample throughout the survey period. My analyses rely on data from the 2001 through 2017 biennial survey waves of the PSID. Data are included for individuals who were both present in the sample during one or more survey waves and designated as either "reference individuals" or as the spouses of reference individuals during any survey wave.

My analyses include only those individuals who are of working-age (between ages 18 and 65) and who are married and in heterosexual partnerships. Sixty-five individuals in same-sex partnerships were excluded from analysis. I also exclude individual-year observations for individuals who newly entered a surveyed family unit in year t; individuals who have negative income; individuals who earn more than $999,999 annually; and individuals who report their salary as an hourly wage or as another amount rather than as an annual sum. Information for individuals with these characteristics is inconsistently available across survey years. A detailed description of the variables included in my analysis is available in Table A2.

4.1 Independent Variables

My analyses include three primary independent variables: breadwinner status, unemployment status, and an interaction between breadwinner status and unemployment status. In addition, I include several control variables in my analyses.

The first independent variable, "Breadwinner," is a binary variable that takes on a value of “1” if an individual is the primary breadwinner in a couple and “0” if not. In my main specification, I classify an individual as a primary breadwinner if his or her total labor income in the year prior to a given survey year was both nonzero and greater than that of his or her spouse. Individuals whose incomes are exactly equivalent to that of their spouses are classified as non-breadwinners. In some tables, this dummy variable is represented as “Not Breadwinner,” and the meanings and data attached to the values of the dummy are flipped.

This analysis focuses on the impact of a binary indicator of breadwinner status on health in light of previous research that suggests that this binary variable most influences the life outcomes of couples. For example, Bertrand et al. (2015) observe that the violation of the male breadwinner status norm negatively impacts marital satisfaction and increases the likelihood of divorce among couples. Yet beyond a binary variable that indicates whether or not a wife outearns her husband, differences in income rank or relative incomes between partners do not predict either marital satisfaction or likelihood of divorce. Since I predict that these declines life satisfaction and increases in marital stress are what translate into negative health outcomes for couples (Section 3), I expect that breadwinner status, rather than relative incomes *per se*, is the variable most relevant to informing health outcomes.

The second independent variable, “Unemployed,” is a binary variable that takes on a value of “1” if an individual was unemployed at *any* point during the prior year and “0” if he or she was *never* unemployed during the prior year.

Third, I analyze the effects of an interaction between “Breadwinner” and “Unemployed” on health. As discussed in section 3, individuals who experience unwanted changes in their breadwinner status may experience more negative health outcomes than individuals who willingly give up breadwinner status due to a “lack of choice” effect. Here, I assume that unemployment is an unwanted and unexpected shock to breadwinner status, and I use the interaction of unemployment status and breadwinner status to assess the impact of changes in unemployment that coincide with changes in breadwinner status on health. An extensive discussion of the plausibility of the assumption that unemployment indeed constitutes an unexpected shock to breadwinner status can be found in Data Appendix A. Further description of the processes used to construct these three key independent variables is available in Table A1.

In addition to these primary variables, I include several control variables in my analyses. First, I include a control for family income, where family income is the sum of the labor incomes of both the male and female partners in a couple. In section 3, I predict that losses of breadwinner status negatively impact the health of individuals, regardless of their family incomes. To assess whether this effect is indeed independent of the effect of income losses on health, I must control for income in my analysis. I control for family income, rather than personal income, because I expect that family income may be more consequential for individuals as they switch between possessing and lacking breadwinner status. For many individuals, losing breadwinner status necessarily connotes a decline in personal income. However, having a healthy family income as a cushion may mitigate some of the adverse effects of this personal income loss on health. To control for the effect of family income on health, I include a variable representing log family income in my empirical models.

Second, as discussed in section 3, a number of demographic variables have been previously linked to health in the literature, including race, age, education, whether an adult has young children, and geography (Deeks et al., 2009; Singh et al., 2017; Jarvis, 1996). I control for these relationships by including several control variables in my models. Time-invariant controls include binary variables that indicate whether or not a person is Black and whether or not a person is White. Additional controls include controls for age; whether or not a man has completed 16 or more years of schooling, a proxy for whether or not he has received a college degree; and a dummy for whether or not a couple has a child aged 17 or younger at home. I also include regional dummies to control for the possibility that health, or access to quality healthcare services that may affect health, varies across space.

4.2 Dependent Variables

My analyses assess the impact of loss of breadwinner status on three sets of outcome variables. These include variables representing (1) subjective health and well-being, (2) physical health, and (3) health behavior. For each variable, I analyze the impact of loss of breadwinner status both on the change in men's health outcomes over time and on their levels of health.

4.2.1 Subjective Well-Being

My analyses include three variables designed to clarify the impact of unemployment-induced losses of breadwinner status on the subjective well-being of individuals.

First, my analyses include an indicator of the mental health status of individuals. The PSID measures mental health using the the K6 Non-Specific Psychological Distress Scale, a screening scale developed by Ronald Kessler. The K6 scale effectively predicts whether individuals meet DSM-IV diagnostic criteria for serious mental illnesses (SMIs), such as anxiety disorders and mood disorders (Kessler et al., 2002, 2003). The K6 scale questions were administered during each of the biennial PSID survey waves from 2001 through 2017, with the exception of 2005. The scale includes six main items:

In the past 30 days, about how often did you feel...

a. so sad, nothing could cheer you up?

b. nervous?

c. restless or fidgety?

d. hopeless?

e. that everything was an effort?

f. worthless?

Respondents score how often they experience these depressive symptoms on a 5-category scale, with possible responses ranging from"All of the Time" (4 points) to "None of the Time" (0 points). The scores for all questions are summed to yield a number between 0 and

24. The cut-point of K6 $\geq$ 13 is an accepted operationalization of the definition of a serious mental illness (SMI), defined as meeting the diagnostic criteria for a DSM-IV disorder besides a substance use disorder during the past 12 months and experiencing significant impairment (Kessler et al., 1998). This cut-point score predicts whether or not an individual will meet the criteria for an SMI with a total accuracy of .92 (Kessler et al., 2003). My analyses collapse the 24-point K6 scale scores into a binary dummy variable, in which scores of 13 or above indicate a strong likelihood that an individual has a clinically significant SMI. This is the same cut-point used by Case and Deaton (2015) to assess the recent growth of morbidity among subpopulations in the United States.

Second, I include a variable, "general subjective health," that uses a Likert scale to illustrate individuals' perceptions of their own general health status. The PSID asks survey respondents to rate their health on a scale of 1-5, with responses ranging from "excellent" to "poor health." I collapse these scale values into a binary variable in which scores of 1-3 indicate "good health" and scores of 4-5 indicate "poor health." This collapsed, binary indicator has been employed to study the impact of unemployment on health in other public health research (Cylus and Avendano, 2017). In addition, this self-rated health scale has been associated with objective health outcomes including risk of subsequent death, suggesting that fluctuations in these ratings may have potentially severe consequences for individuals (Burstrom, 2001).

Finally, I include a third subjective health variable, "health declined or improved," that illustrates how men compare their present health to their health two years ago. The PSID includes an item that explicitly asks respondents to state if their health is "better, about the same, or worse" than it was approximately two years ago. This measure offers an advantage for my longitudinal analyses, which assess how men's health changes over two-year periods that begin prior to their breadwinner status loss and conclude afterward. In explicitly asking men to compare their health before and after they lose their breadwinner status, this measure may allow for an unusually detailed comparison of variation in men's health over time. For example, an analysis of the change in self-reported health Likert scale values for a man who reports "poor" health during both of two survey waves might suggest that this man's health has remained the same over time; in contrast, the same man is able to report that his health became "worse" if he feels that it remained "poor," but became even poorer, over time.

4.2.2 Physical Health

To provide a holistic picture of the impact of loss of breadwinner status on health, I also include outcome variables that describe the physical health of respondents. The first variable, "hypertension," is a binary variable that indicates whether or not a man reports that his doctor has ever informed him that he has high blood pressure or hypertension. The second variable, "obese," is a binary variable that indicates whether a man's BMI renders him "obese." Men are classified as obese if their BMI values fall within World Health Organization (2000) classifications for class I, class II, and class III obesity, which use BMI cutpoints of 30, 35, and 40, respectively. BMI values are calculated for each man based on self-reported height and weight.

Hypertension and obesity are not often included as outcomes of interest in scholarship on "deaths of despair" and "diseases of despair," which has instead frequently focused on suicide, drug and alcohol poisoning, and liver diseases (Case and Deaton, 2015, 2017). However, if the objective of "diseases of despair" research is to determine how social, environmental, medical, and other factors have contributed to recent increases in mortality, this exclusion may be unfounded. For example, a substantial slowdown in the rates of decline of mortality related to heart disease has contributed to the recent increase in mortality among U.S. Whites relative to Black individuals living in the U.S. and residents of other wealthy countries (Case and Deaton, 2017) (p. 412). Hypertension and obesity are both risk factors for heart disease, and increases in these health factors should be considered as potential causes of growing mortality among U.S. Whites. This possibility has recently gained recognition in scholarship on deaths and diseases of despair, which has noted that "obesity and over-eating" may be "in part responsible for the reversal in the decline of deaths from heart disease" (Case and Deaton, 2018).

4.2.3 Health Behavior

Finally, I explore the impacts of changes in breadwinner status on health behaviors, including substance use. My primary health behavior variable, "binge drinking," indicates whether men who drink alcohol typically engaged in heavy drinking. The Substance Abuse and Mental Health Services Administration (2020) defines binge drinking for men as drinking five or more drinks on the same occasion on at least 1 day during the past 30 days. The PSID measure of alcohol use asks respondents to indicate the number of drinks that individuals typically consumed per day, rather than per occasion, on the days that they drank during the past year. Here, I classify men as having participated binge drinking if the number of drinks that they typically consumed on the days that they drank was five or greater.

4.3 Summary Statistics

Tables B2 through B6 report basic summary statistics for the independent and dependent variables included in my models. My analyses are performed on unbalanced panels. New individuals enter into the PSID data pool every two years throughout the period over which my analysis is conducted, and other individuals leave the panel as they die or leave PSID families. Further, each of my empirical models includes different variables. Since data are not available for every individual for every variable and every year, the available sample sizes vary with the variable requirements for each empirical model.

To preserve as much data as possible, I have chosen to run each of my models on the largest available sample of individual-year observations, rather than excluding some observations from my sample pool so that each model runs on the same sample. In Tables B2 through B6, I report separately the means and standard deviations of the major variables included in each model. In these tables, "Observations" refers to the number of year t

individual-year observations used in each model.

The data used in this analysis are not representative of the broader United States population. The information required to complete complex sample survey variance estimation is not available for PSID family-level survey data. Summary statistics describe only those individuals included within the PSID sample.

5 Empirical Strategy

My empirical strategy relies on logistic and multinomial logistic regressions to assess the impact of losses of breadwinner status on the health of men. Below, I develop two empirical models, each of which assists in illuminating particular nuances in the relationship between breadwinner status and men's health. First, I develop a fixed effects model to assess the impact of *lacking* breadwinner status on men's health. Second, I use a first differences model to examine the impact of *losing* breadwinner status on men's health.

5.1 Fixed Effects Model

First, I develop a fixed effects model to assess the relationship between men's levels of health and their breadwinner status. My fixed effects specification for each individual i is as follows:

$$\begin{aligned} Health\ddot{}_{it} = &\beta_1 lnFamInc\ddot{o}me_{it-1} + \beta_2 Unempl\ddot{o}yed_{it-1} + \beta_3 Breadw\ddot{i}nner_{it-1} + \\ &\beta_4 Breadw\ddot{i}nner_{it-1} * Unempl\ddot{o}yed_{it-1} + \beta_5 \ddot{\mathbf{X}}'_i + \beta_6 \ddot{\mathbf{Y}}'_{it-2} + \ddot{u}_{it} \end{aligned} \tag{1}$$

In this expression, variables are indexed by individual (i) and time (t). The inclusion of an umlaut above a given variable indicates that the variable has been time-demeaned. For example, $Health\ddot{}_{it} = Health_{it} - \overline{Health}_{it}$, where $\overline{Health}_i$ is the mean health outcome for each individual i. The outcome variable $Health_{it}$ is the level of health that an individual experienced in a given year t. On the right-hand side, variable $lnFamIncome_{it-1}$ is the log of lagged family income, where family income is the sum of the labor incomes of both the male and female partners in a couple in year $t-1$. $Unemployed_{it-1}$ is a dummy variable that takes on a value of "1" if the male partner was unemployed at any point during year $t-1$ and "0" if not. $Breadwinner_{it-1}$ is a dummy variable that takes on a value of "1" if a male partner outearned his wife during year $t-1$ and a value of "0" if her income was greater than his or if their incomes were equivalent. The coefficient β_4 reports the interaction between $Unemployed_{it-1}$ and $Breadwinner_{it-1}$. I lag independent variables as a check against potential reverse causality between health and breadwinner status and unemployment.

The vectors $\mathbf{X}_i'$ and $\mathbf{Y}_{it-2}'$ contain controls for the characteristics of individuals and their families. The vector $\mathbf{X}_i'$ includes controls for the time-constant characteristics of individuals, including whether a person is Black and whether a person is White. The vector $\mathbf{Y}_{it-2}'$ includes start-of-period controls for time-varying traits of individuals and their families in year $t-2$. These controls include variables representing an individual's age, whether or not a man has completed 16 or more years of schooling, and a dummy for whether or not a couple has a child aged 17 or younger at home. It also includes regional dummies.

This model examines the health impacts of longitudinal, within-individual variation in the breadwinner status of men over time. For each individual i, the fixed effects estimators or model coefficients report the relationship between within-individual variation in employment, income, and breadwinner status across time and within-individual, longitudinal variation in health. The average impact of these within-individual effects across individuals is then obtained by pooling these individual-level estimators. In this sense, this fixed-effects model approximates a differences-in-differences approach, examining the impact of both within- and across-individual variation in breadwinner status on health.

Fixed effects estimation assists in eliminating unobserved heterogeneity that may result from omitting unobserved, time-constant variables from my empirical model. Men may possess unobserved characteristics that lead them both to be more likely to be breadwinner and to have excellent health, such as character traits that lead them to be unusually "motivated" or "diligent." These characteristics may not be randomly distributed across men, and failing to control for them may bias the coefficient on $Breadwinner_{it-1}$. Fixed effects transformation controls for these unobserved traits if they are time-invariant. By time-demeaning each variable, the fixed effects transformation succeeds in removing individual-level, fixed or time-constant error from the model. Accordingly, the potential existence of unobserved, time-constant factors that may affect men's health does not threaten to render the coefficients of this model biased or consistent.

Since fixed effects models eliminate error related to unobserved, time-constant variables, most fixed effects models do not include any observed variables that are always or typically fixed for individuals across time, such as race and region. However, I choose to include these variables in my model to facilitate understanding of how cross-sectional variation in individuals' fixed demographic characteristics impacts their health.

For fixed effects estimators to be unbiased, the time-varying error, u_{it}, must be uncorrelated with each explanatory variable across all time periods, such that $E(u_{it}|\mathbf{X}_i, a_i) = 0$. This assumption cannot be satisfied unless the time-varying explanatory variables are strictly exogenous, which may not always be the case. For example, labor market fluctuations due to events such as the 2009 H1N1 pandemic and other unobserved time-varying factors may lead certain individuals to be both more likely to become unemployed or lose breadwinner status and more likely to experience worse health in certain years. These effects may be unevenly distributed across individuals. However, beyond manipulating breadwinner status in an experimental context, a task with distressing ethical implications, little can be done to control for these time-varying characteristics. By controlling for the time-constant characteristics of individuals, this fixed effects model provides a next-best means of obtaining unbiased and consistent model coefficients.

The fixed effects model has an important drawback. Since fixed effects models time-demean data across years for individuals, they are not able to make use of data for individuals who are only included within the dataset for a single year. Using a fixed effects model results in a loss of data, reflected in the small number of observations listed for fixed effects results in the tables in Appendix B. Random effects estimation, an alternative to fixed effects estimation that preserves data for individuals included within the dataset for only a single year, is explored in section 6.2.

5.2 First Differences Model

The fixed effects transformation in subsection 5.1 assists in eliminating a critical source of bias in coefficient estimates: time-constant error that correlates with key explanatory variables. First differences transformation also eliminates this error, but rather than time-demeaning data to rid of the error, this estimation strategy differences across adjacent time periods. In many cases, implementing both fixed effects and first differences models may be unnecessary, as the two models may yield similar results. However, the structure of my data allows me to yield additional insight into the dynamics of the relationship between breadwinner status and health by implementing both fixed effects and first differences strategies, for reasons that I will discuss below.

My first differences specification is as follows:

$$\begin{aligned}\Delta Health_{it} = & \beta_0 + \beta_1 \Delta lnFamIncome_{it-1} + \beta_2 \Delta Unemployed_{it-1} + \\ & \beta_3 \Delta Breadwinner_{it-1} + \\ & \beta_4 \Delta Breadwinner_{it-1} * \Delta Unemployed_{it-1} + \\ & \beta_5 \mathbf{X}'_i + \beta_6 \mathbf{Y}'_{it-2} + \epsilon_{it}\end{aligned} \tag{2}$$

In this model, $\Delta Health_{it}$ represents the change in the health outcomes that an individual experienced between a given year $t-2$ and year t. In contrast, all of the differenced *explanatory* variables in the model represent the change in the variable between a given year $t-2$ and year $t-1$. For example, $\Delta lnFamIncome_{it-1}$ is the change in a family's log income between year $t-2$ and year $t-1$. The same is true for $\Delta Unemployed_{it-1}$, $\Delta Breadwinner_{it-1}$, and the interaction of these variables. By examining the impact of *lagged* breadwinner and unemployment status changes on health, I avoid potential simultaneity issues that might occur if both health and breadwinner status change simultaneously as the result of changes in an omitted variable. In a departure from a standard first differences model, I also include two vectors of individual and family control variables, $\mathbf{X}_i'$ and $\mathbf{Y}_{it-2}'$, which comprise the same controls for race, schooling, children at home, and region as in equation 3. β_0 is an intercept term, and ϵ_{it} is an error term.

The unique, lagged structure of the differenced explanatory variables in this model provides special insight into the dynamics underlying the relationships between breadwinner status and health. The coefficients on $\Delta Breadwinner_{it-1}$ in the fixed effects model presented in subsection 5.1 report the mean impact of within-individual variation in breadwinner status on the health of individuals. Many men are included in the dataset multiple times, across multiple survey years, so fixed effects analysis assists in facilitating understanding of how the typical man's health varies between years when he is the primary breadwinner versus when he is not the breadwinner. However, the fixed effects model presented in subsection 5.1 does not assess the effect of *immediate losses* of breadwinner status on men's health. In contrast with the fixed effects model, which pools the average health effects of lacking or possessing breadwinner status for each man over time, the first differences model presented here examines the impact of immediate shifts in breadwinner status between years $t-2$ and $t-1$ on changes men's health between years $t-2$ and t. Men may react differently to situations in which they experience immediate losses of breadwinner status than they do to situations in which they are not the breadwinner in their household, but perhaps have maintained and become acclimated to this status over the course of several years. In directly examining the impact of immediate losses of breadwinner status on men's health, the first differences model provides a more direct depiction of how *losing* breadwinner status affects men's health.

In my first differences analyses, I allow the primary outcome variable, $\Delta Health_{it}$, to take on multiple values. For example, between years t and $t-2$, a person's health may remain "good," remain "bad," improve, or decline. To provide a full picture of the impact of changes in breadwinner status and unemployment status on changes in health, I use multinomial logit models in my first differences analyses.

The first differences model has the most demanding data requirements of the models included in this paper, requiring information about an individual's health for two adjacent survey waves, or in both a given year t and year $t-2$. In contrast, the fixed effects approach described in subsection 5.1 requires information on health in two or more years t, regardless of whether these years are adjacent survey waves. For three health outcomes (serious mental illness, hypertension, and obesity), sample sizes for individuals who had health information in both years t and $t-2$ were insufficiently large to achieve model convergence for the first differences. First differences models were not reported for these health outcomes. Table B7 provides detailed, two-way frequency tables for the first differences models included in this paper.

A discussion of the differences in econometric assumptions between the first differences and fixed effects models can be found in Data Appendix A.

6 Results

Results regarding the impact of breadwinner status on subjective well-being, physical health, and health behaviors are reported below, alongside several robustness checks.

6.1 Main Results

Subjective Well-Being

My results suggest that losses of breadwinner status have negative or negligible effects on subjective well-being, depending on the measure of well-being.

First, my fixed effects analysis suggests that breadwinner status significantly impacts men's mental health. Table B8 reports the impact of unemployment status, breadwinner status, and their interaction on a binary variable that indicates whether or not men likely have a serious mental illness (SMI). Given the inclusion of an interaction term in this table, the interpretation of model coefficents is somewhat complex. For each explanatory variable, "Unemployed," "Not Breadwinner," and "Unemployed × Not Breadwinner," model coefficients are reported as the ratios of the odds that members of the relevant breadwinner status/unemployment group will have an SMI *relative* to the odds that members of a reference group comprised of *employed breadwinners* have SMIs. The model coefficients for variable "Unemployed" report the likelihood that men who are *unemployed breadwinners* have an SMI, relative to likelihood that employed breadwinners have SMIs. The coefficients for the variable "Not Breadwinner" indicate the likelihood that *employed non-breadwinners* has an SMI, relative to employed breadwinners. Finally, the interaction term, "Unemployed × Not Breadwinner," reports the likelihood that *unemployed non-breadwinners* have SMIs, relative to employed breadwinners. Further discussion of how to interpret these model coefficients can be found in Table A3.

Drawing on this interpretive guide, Table B8 suggests that lacking breadwinner status negatively affects men's mental health, though only in certain situations. In a fixed effects analysis of the impact of "Not Breadwinner" on mental illness risk, I find that men who are employed non-breadwinners are 1.977 times as likely to have a K6 scale score that indicates that they likely have a mental illness, relative to employed breadwinners. This result is significant at the 10 percent level ($z = 1.68$). The magnitude of the effect of breadwinner status on mental health is impressive, outweighing the magnitude of the effects of unemployment and income on mental health. In contrast, the interaction of unemployment and breadwinner status does not significantly affect mental health. Men who are unemployed and who lack breadwinner status are not significantly more likely to have a mental illness than employed breadwinners. Importantly, the coefficients reported for "White" and for the regional dummies in this table are implausibly large. The inclusion of these variables in the model may represent a model misspecification, and they may have altered the values of the other model coefficients.

Table B9 reports the impact of unemployment and breadwinner status on a binary variable that indicates whether men indicate having either "good" or "poor" subjective health. The results indicate that men who are not breadwinners are typically, though not always, less likely to report having "good" subjective health. Employed non-breadwinners are substantially less likely to have "good" health then employed breadwinners. In the fixed effects approach, employed non-breadwinners are only 0.773 times as likely to have "good" health as employed breadwinners, a highly significant finding ($z = -2.63$). However, the interaction between unemployment and lack of breadwinner status is insignificant, suggesting that men who are unemployed non-breadwinners do not have substantially different subjective health from employed breadwinners.

Notably, the fixed effects approach indicates that age also significantly affects health. On average, increasing age by a year render individuals 0.892 times as likely to have "good" health relative to having "poor" health, all else equal. This result holds broadly in Table B10, which explores the impact of changes in breadwinner status on changes in subjective health using a first differences model. Here, older individuals are more likely to report any other health outcome—maintaining "poor" health over two years, experiencing improving health over two years, or experiencing declining health over two years—besides maintaining consistently "good" health over two years. For older individuals, health becomes both less stable over time and less likely to remain consistently "good."

In contrast with the fixed effects results reported in Table B9, the first differences results reported in Table B10 indicate that changes in unemployment status and breadwinner status negligibly affect health. The results from the fixed effects model in Table B9 indicate that within-individual changes in breadwinner status do impact health: on average, individuals are more healthy when they are breadwinners when they are not. However, the first differences model in Table B10 suggests that this variation is not visible over the course of brief, two-year periods during which individuals experience immediate losses of unemployment status, breadwinner status, or both.

Table B11 reports the impact of changes in unemployment and breadwinner status on a categorical variable that indicates whether men report that their health has gotten "better," become "worse," or remained "about the same" over the past two years. Here, changes in unemployment, changes in breadwinner status, and the interaction of these changes have no impact on the likelihood that men report that their health has gotten "*better*" relative to remaining "about the same" over the past two years. However, men who become unemployed and experienced no change in their breadwinner status are substantially more likely to report that their health became "worse" over the past two years relative to remaining "about the same," compared to men who both did not become employed and experienced no change in their breadwinner status. These men were 1.681 times as likely to report worsening health, a highly significant result ($z = 3.08$). Men who lost breadwinner status were also more likely to report that their health had become "*worse*." Relative to employed men who experienced no change in breadwinner status, employed men who lost breadwinner status were 1.474 times ($z = 3.69$) as likely to report worsening health compared to unchanging health. However, the interaction between unemployment and breadwinner status does not significantly affect changes in health.

Notably, both Black men and men with 16 or more years of education were less likely to report that their health had declined relative to two years ago, as opposed to remaining the same over time. Black men were 0.594 times as likely to report worsening health relative to stable health, a result significant at the 1 percent level ($z = -3.25$). This follows findings from Case and Deaton (2017), who observe that the health of Black individuals in the United States has largely not declined over the past 20 years. However, being "White" did not significantly affect the likelihood of reporting worsening health, a finding that contrasts with opposing findings by Case and Deaton (2017). Individuals with 16 or more years of education were 0.742 times as likely to report worsening health relative to stable health, another highly significant finding ($z = -4.17$). Neither being Black nor having completed

16 or more years of education affected men's likelihood of reporting that their health had improved over time.

Physical Health

Results for the impact of breadwinner status on physical health suggest that breadwinner status has mixed effects on health, negligibly impacting men's likelihood of having hypertension but decreasing their likelihood of being obese.

First, results from the fixed effects model in Table B12 indicate that breadwinner status does not significantly affect the prevalence of hypertension among men. Neither being unemployed nor lacking breadwinner status affects the likelihood that men report having hypertension. In contrast, having a higher log family income renders men significantly less likely to report having hypertension (0.956; $z = -2.46$). Older men are more likely to have hypertension, a highly significant result (1.295, $z = 30.51$).

Table B13 indicates that breadwinner status significantly affects obesity among men. The fixed effects specification in column 2 indicates that compared to employed breadwinners, men who are employed non-breadwinners are 0.773 times as likely to be obese ($z = -2.90$). In contrast, older individuals are significantly more likely to be obese (1.106, $z = 14.63$). Unemployment status and the interaction of unemployment status and breadwinner status both have negligible effects on the prevalence of obesity among men.

These results invite multiple potential explanations. Employed, non-breadwinning men may have less strenuous jobs or may work fewer hours than employed breadwinning men, leaving them more time for exercise and lose weight. Alternatively, these men may be able to cultivate healthier eating habits if they work shorter shifts and have more spare time to cook. Research on the impact of recessions on health suggests that individuals exercise more and eat more healthfully when the economy is weak, and these results may inform how men react to having attenuated work hours at the micro-level (Ruhm, 2000). On the other hand, unemployed non-breadwinners may not see these positive BMI benefits of *not* maintaining breadwinner status if stress or other adverse reactions to unemployment impact their desire or ability to engage in weight-reducing exercise or healthy eating activities.

Health Behavior

Finally, I explore the impact of breadwinner status on the health behavior of men. Table B14 reports the relationship between breadwinner status and binge drinking among men. The fixed effects specification indicates that employed, non-breadwinning men are 1.241 times as likely to engage in binge drinking as employed breadwinners ($z = 3.39$). Men with 16 or more years of education are also more likely to binge drink (1.513, $z = 2.71$), while older men (0.829, -35.44) and White men (0.265, $z = -4.56$) are substantially less likely to engage in binge drinking. The coefficient on "White" is especially striking: men who are White are almost only a quarter as likely to binge drink as men who are not White, suggesting that binge drinking is disproportionately concentrated among non-White men.

Table B15 reports the impact of changes in breadwinner status and unemployment status on changes in men's binge drinking habits. Here, losses of breadwinner status significantly affect the likelihood that men either continue binge drinking consistently or stop binge drinking relative to never engaging in binge drinking. However, they do not affect whether or not men start binge drinking. The coefficient for individuals who "lost" breadwinner status in column 1 indicates that employed men who lose breadwinner status are 1.301 times more likely to continue binge drinking as opposed to never engaging in binge drinking than employed men who experienced no change in breadwinner status, a highly significant result ($z = 2.49$). However, the coefficient on "lost" breadwinner status in column 3 indicates that these employed, non-breadwinning men are also 1.262 times ($z = 1.89$) more likely to *stop* binge drinking, as opposed to never engaging in binge drinking. Non-breadwinning employed men may be more likely to drink than breadwinning employed men in general, rendering them more likely to either continue or stop binge drinking. Other variables related to breadwinner and unemployment status have little impact on binge drinking patterns.

6.2 Robustness Checks

To confirm the validity of my results, I conduct three robustness checks. First, I compare the results from the fixed effects model to results from a pooled logistic regression model. Second, I compare my fixed effects estimation strategy to a random effects strategy to assess which specification is warranted in my analysis. Finally, I compare results for men to results for women to establish whether the trends that I identify in section 6.1 are unique to men.

6.2.1 Pooled Logistic Regression Model

The fixed effects specification described in subsection 5.1 has several advantages: it controls for unobserved heterogeneity, and it examines variation in health among individuals both longitudinally and cross-sectionally. However, this model cannot make use of data for individuals who are included in the dataset during only one survey wave. In contrast, a simple, pooled logistic regression model can make use of data on every individual, regardless of the number of years for which he or she is included in the dataset. Here, I briefly describe this alternative model and discuss the advantages and costs of using this model relative to the fixed effects model.

Below, I present a pooled logistic regression model that uses maximum likelihood estimation to examine the relationship between breadwinner status and men's health. Pooling data on health, breadwinner status, and employment status, and other personal characteristics across all men, this model assesses how cross-sectional variation breadwinner status affects variation in men's health. This model is specified as follows:

$$\begin{aligned} Health_{it} = \beta_0 + \beta_1 lnFamIncome_{it-1} + \beta_2 Unemployed_{it-1} + \beta_3 Breadwinner_{it-1} + \\ \beta_4 Breadwinner_{it-1} * Unemployed_{it-1} + \beta_5 \mathbf{X}_i^{'} + \beta_6 \mathbf{Y}_{it-2}^{'} + \epsilon_{it} \end{aligned} \tag{3}$$

The meanings of the variables and vectors of variables reported here are the same as those in equation 1. Since men may be included in the dataset multiple times across survey years, I cluster standard errors by individual. The results for the pooled logistic regression approach for men are reported in tables B8, B9, B12, B13, and B14. In general, comparing the results from this approach with those from the fixed effects approach in subsection 5.1 suggests that direction of the effect of key coefficients on health remains the same between models, while effect size varies between approaches. For example, lacking breadwinner status significantly increases one's likelihood of developing a serious mental illness and decreases one's likelihood of having "good" subjective health in both the fixed effects and pooled logistic regression modeling approaches (Tables B8 and B9). However, the magnitudes of the effect size of breadwinner status on health are larger in the pooled logistic regression model for both health outcomes. The relationship between the coefficients reported for each of the two models is less straightforward for the other health outcomes. In both models, lacking breadwinner status increases the likelihood that men have hypertension, but this effect is significant only in the logistic regression approach (Table B12). In contrast, although lacking breadwinner status has a significant, inverse relationship with obesity in both models, the effect size is larger for the fixed effects approach (Table B13). Finally, the direction of effect of breadwinner status on binge drinking differs between models. The pooled logistic regression approach suggests that lacking breadwinner status decreases the prevalence of binge drinking, while the fixed effects approach suggests that lacking breadwinner status renders men 1.241 times as likely to binge drink (Table B14).

The differences in coefficient size and direction between the two models may result from one of two factors: unobserved heterogeneity or sample selection. First, in contrast with a fixed effects approach, the pooled logistic regression approach cannot control for unobserved heterogeneity. In equation 3, the composite error, ϵ_{it}, can be written as $\epsilon_{it} = u_{it}+a_i$, where u_{it} is the time-varying or idiosyncratic error and a_i is the time-constant error. For estimates of key coefficients to be consistent and unbiased, ϵ_{it} (and by extension, a_i) must be uncorrelated with each explanatory variable: any unobserved, time-constant characteristics of the men included in this dataset must not correlate with the observed characteristics controlled for in this model, such as their income and breadwinner status. Unfortunately, this restriction is difficult to satisfy. For example, men may be more likely to have higher incomes and to be the breadwinner if they are more motivated or hardworking, factors that are difficult to include as formal control variables. These characteristics may not be randomly distributed across men, and they may contribute to unobserved heterogeneity in the dataset. The differences in coefficients between the fixed effects and pooled logistic regression coefficients may be due to unobserved heterogeneity in the dataset, which might bias the pooled logistic regression coefficients.

Second, coefficients may differ between the two models due to sample selection. The pooled logistic regression model uses information from the full sample of individuals available from the PSID during the relevant data years. In contrast, the fixed effects approach eliminates individuals who are only featured in the dataset for a single year. In some cases, this exclusion substantially reduces the sample size for the fixed effects approach: while the pooled logistic regression model for the impact of breadwinner status on serious mental illness prevalence draws on over 10,000 individual-year observations, for example, the fixed effects approach draws on a sample comprised of only 413 individual-year observations (Table B1). The fixed effects approach will suffer from sample selection bias if the observed or unobserved characteristics of the fixed effects sample differ from those for the pooled logistic regression sample. The coefficients in the fixed effects approach may differ from those for the pooled logistic regression approach as a result of this bias.

The fixed effects approach remains my primary specification (as opposed to the pooled logistic regression approach) because I expect that sample selection has a relatively limited effect on the coefficients reported for my fixed effects approach. For most of the health outcomes studied in this paper, the observed characteristics of the individuals in the fixed effects sample are broadly similar to those of the individuals included in the pooled logistic regression sample (see summary statistics for each model in tables B2, B3, B4, B5, and B6). If unobserved characteristics of individuals that might bias observed coefficients are similarly distributed between samples, there is little reason to expect that the fixed effects model produces biased results. Notably, sample selection may be more of a problem for the analysis of serious mental illness (see table B1), which has the largest percentage loss of data when using the fixed effects approach relative to the pooled logistic regression approach of all health outcomes. For this health outcome, a closer examination of the relative benefits of the fixed effects versus the pooled logistic regression approach may be warranted. Otherwise, however, I hypothesize that the unobserved heterogeneity associated with the pooled logistic regression model will bias the model coefficients to a greater extent than any sample selection bias associated with the truncated fixed effects samples. For this reason, the fixed effects model is my preferred empirical approach.

6.2.2 Random Effects

The fixed effects estimation strategy introduced in subsection 5.1 transforms the simple logistic regression model to eliminate time-constant error, ensuring that the presence of this error does not threaten the unbiasedness and consistency of model coefficients. For this reason, a fixed effects model is my preferred empirical approach. However, if time-constant error is in fact *uncorrelated* with explanatory variables, transforming the model with fixed effects results in inefficient estimators. Random effects estimation strategies are preferred to fixed effects when time-constant error is uncorrelated with explanatory variables, as these strategies do not require costly losses of data for individuals for whom observations are only available for a single data year. Here, I assess whether my choice of a fixed effects estimation strategy was warranted or whether random effects estimation may provide a more efficient operationalization of my research question.

Random Effects Estimation

Random effects estimation strategies assume that time-constant error is uncorrelated with the explanatory variables in a model. If this assumption is accurate, fixed effects transformations are unnecessary, as random effects models can produce unbiased and consistent estimators while preserving data eliminated in a fixed effects transformation. Below, I produce a random effects model and test whether an application of this model to my data produces significantly different results from a fixed effects model.

My random effects specification involves a transformation of the pooled logistic regression model presented in equation 3. In this equation, the composite error term, ϵ_{it}, can be written as $\epsilon_{it} = u_{it} + a_i$, where u_{it} is the time-varying or idiosyncratic error and a_i is the time-constant error. Fixed effects models remove the composite error in each time period, a_i, from ϵ_{it}. The core assumption underlying random effects estimation, that a_i is uncorrelated with all explanatory variables, renders this exclusion unwarranted. However, if one simply includes a_i in a pooled logistic regression without transforming the regression at all, one can expect that the values of ϵ_{it} will be serially correlated over time. The correlation between the values of the error term ϵ_{it} between time periods t and s in a pooled logit model can be written as $Corr(\epsilon_{it}, \epsilon_{is}) = {\sigma^2}_a/({\sigma^2}_a + {\sigma^2}_u)$, $t \neq s$, for which ${\sigma^2}_a = Var(a_i)$ and ${\sigma^2}_u = Var(u_i)$. Here, the serial correlation in the error term, $Corr(\epsilon_{it}, \epsilon_{is})$, is necessarily positive. For this reason, the pooled standard errors of the simple logit model are incorrect.

To eliminate this serial correlation, random effects estimation transforms the simple pooled logit model by quasi-demeaning each variable. To transform equation 3, we can define

$$\theta = 1 - [{\sigma^2}_u/({\sigma^2}_u + T{\sigma^2}_a)]^{1/2}, \tag{4}$$

where T is the total number of time periods. Transforming equation 3 to eliminate serial correlation in the standard errors yields a random effects model:

$$\begin{aligned} Health_{it} - \theta\overline{Health}_i = {} & \beta_0(1-\theta) + \beta_1(lnFamIncome_{it-1} - \theta\overline{lnFamIncome}_i) + \\ & \beta_2(Unemployed_{it-1} - \theta\overline{Unemployed}_i) + \beta_3(Breadwinner_{it-1} - \theta\overline{Breadwinner}_i) + \\ & \beta_4(Unemployed_{it-1} - \theta\overline{Unemployed}_i) * (Breadwinner_{it-1} - \theta\overline{Breadwinner}_i) + \\ & \beta_5(\mathbf{X}'_i - \theta\overline{\mathbf{X}}'_i) + \beta_6(\mathbf{Y}'_{it-2} - \theta\overline{\mathbf{Y}}'_i) + (\epsilon_{it} - \theta\overline{\epsilon}_i) \end{aligned} \tag{5}$$

In this equation, data for each variable are quasi-demeaned. Rather than subtracting time averages from each variable, as in a fixed effects model, the random effects model subtracts a fraction of the time average from each variable. The values of the relevant fractions depend on ${\sigma^2}_u$, ${\sigma^2}_u$, and T. Results from random effects analyses of the impact of breadwinner status and unemployment status on health are reported in column 3 of each Tables B8, B9, B12, B13, and B14.

The accuracy of the random effects model depends on the accuracy of its core assumption, that the time-constant error, a_i is uncorrelated with the explanatory variables for all past, present, and future time periods for each individual. If model coefficients in a random effects specification differ significantly from those in a fixed effects specification, fixed effects assumptions may be warranted. Below, I describe how a Hausman test can assist in distinguishing whether a fixed effects estimation strategy may be warranted or whether random effects assumptions are sufficient.

Hausman Test

The Hausman test, first proposed by Hausman (1978), tests for statistically significant differences in the coefficients of time-varying variables between random and fixed effects models. In this test, the null hypothesis, H_0, is that a random effects treatment is preferred, or that the use of random effects instead of fixed effects does not imply a model misspecification. The alternative hypothesis, H_a, is that a random effects model is a misspecification, and a fixed effects model is preferred. Rejecting H_0 suggests that a fixed effects transformation is warranted to avoid endogeneity problems related to the failure to eliminate time-constant error from the model.

To test whether fixed or random effects estimation strategies are warranted, I perform a Hausman test to compare the fixed effects and random effects empirical models for each health outcome included in this paper. In each case, I conduct Hausman tests on modified versions of the fixed effects model presented in equation 1 and the random effects model in equation 5, maintaining the inclusion of the transformed variables $lnFamIncome$, *Unemployed*, *Breadwinner*, and *Unemployed* $\times$ *Breadwinner* but omitting all other control variables. Results from the Hausman test are reported below.

Table 1: Results from Hausman Test

Model	Chi-Sq Statistic	P-values
Serious Mental Illness	14.73	0.0053
Subjective Health	392.76	0.0000
Hypertension	180.35	0.0000
Obesity	28.51	0.0000
Binge Drinking	196.74	0.0000

The results from each Hausman test strongly support a rejection of H_0, suggesting that a random effects model is a misspecification and a fixed effects model is warranted.

6.2.3 Results for Women

Results for women are reported in Tables B16 through B17. Depending on the health outcome at hand, some results for women are remarkably similar to those for men. Other results indicate that breadwinner status may have less of an impact on women's health than men's health.

Subjective Well-Being

Results for the impact of breadwinner status on women's subjective well-being suggest that maintaining status as primary earner affects the health of both men and women similarly.

Table B16 reports the impact of breadwinner status on the prevalence of serious mental illnesses (SMIs) and "good" subjective health among women. While a fixed effects approach indicates that lacking breadwinner status moderately increases the likelihood that men have SMIs (1.977, $z = 1.68$), it does not significantly affect the mental health of women. Indeed, though the fixed effects approach for women draws on a slightly larger sample size ($n = 930$) than that for men ($n = 413$), *none* of the fixed effects coefficients in the model for women affect their likelihood of developing an SMI.

In contrast, the fixed effects approach indicates that non-breadwinning women are substantially less likely to have "good" subjective health relative to having "poor" health. The magnitude of the effect of lacking breadwinner status on women's health, 0.757 ($z = -2.71$) is remarkably similar to that for men (0.773, $z = -2.63$). In addition, the "Unemployed × Not Breadwinner" interaction has a significant effect on women's likelihood of having "good" subjective health. Surprisingly, compared to employed, breadwinning women, unemployed, non-breadwinning women are 1.637 times as likely to have "good" health relative to "poor" health ($z = 1.65$).

Table B17 reports the impact of breadwinner status on the likelihood that women report that their health is either "better" or "worse" than two years ago, as opposed to remaining "about the same." Here, results regarding women's health diverge sharply from results for men. While employed men who lose breadwinner status are substantially more likely to report having "worse" health relative to health that remained "about the same" (1.474, $z = 3.69$), losing breadwinner status does not significantly impact the likelihood that women report declining health. However, while gaining breadwinner status does not affect men's health, it improves women's health: employed women who gained breadwinner status were 0.801 times as likely to report "worse" health relative to stable health ($z = -1.83$). Further, while losing breadwinner status does not impact the likelihood that men experience improved or "better" health, women who lose breadwinner status are 1.311 times as likely to report "better" health relative to stable or unchanging health ($z = 2.21$). This paints a contradictory picture for women: gaining breadwinner status decreases the likelihood that women report worsening health, but losing breadwinner status increases the likelihood that women report improving health. Both changes to breadwinner status appear to affect health positively.

What explains the divergence in trends between men and women and the seemingly contradictory trends regarding women's health responses to changes in their breadwinner status? One potential explanation is that men are especially averse to losses of breadwinner status, so they react strongly to losing breadwinner status but experience minimal health boosts when they gain it. Women, on the other hand, may not care whether or not they are breadwinners *per se*, but they may value having the flexibility to either give up breadwinner status to perform the normatively female role of taking care of a child or to become the breadwinner when they desire additional income. If this is true, women might experience positive health boosts when their breadwinner status changes, regardless of the direction of the shift.

Interestingly, while men who become unemployed are substantially more likely to report "worse" health relative to stable health (1.681, $z = 3.08$), becoming unemployed does not significantly affect the health of women. As for men, age increases the likelihood that women report "worse" health (1.023, $z = 6.66$), and having 16 or more years of education decreases the likelihood that women report worsening health (0.724, -4.34).

Physical Health

Results for the impact of breadwinner status on physical health suggest that breadwinner status typically affects women's physical health less intensely than it does the health of men.

Table B18 reports the impact of breadwinner status on the prevalence of hypertension and obesity among women. Results from the fixed effects approach in column 2 indicate that breadwinner status does not significantly affect the likelihood that women report having hypertension. This is true also for men. In contrast, for both women and men, age strongly predictor of hypertension status. If a woman's age were to increase by 1 year, her risk of having hypertension would be expected to increase 1.235 times, holding all else constant ($z = 23.66$). Older men are likewise more likely to have hypertension (1.295, $z = 30.51$). Being Black also substantially increases the likelihood that women have hypertension (10.98, $z = 2.75$).

For men, lacking breadwinner status substantially *decreases* one's likelihood of being obese (0.773, $z = 2.90$). In contrast, fixed effects results indicate that breadwinner status does not significantly affect the likelihood that women are obese. However, while unemployment does not impact the likelihood that men are obese (see B13 column 2), unemployment substantially decreases the likelihood that women are obese (0.585, $z = -1.85$). As for men, older women are more likely to be obese (1.072, $z = 10.12$).

Health Behavior

Finally, I explore the impact of breadwinner status on the prevalence of binge drinking among women. Table B19 reports the impact of breadwinner status on a binary variable that indicates whether or not women engage in binge drinking, or drinking four or more drinks per day. While a fixed effects approach indicates that employed, non-breadwinning men are more likely to binge drink than employed, breadwinning men (1.241, $z = 3.39$; Table B14, column 2), the fixed effects approach for women in column 2 indicates that lacking breadwinner status does not significantly affect the likelihood that women engage in binge drinking. However, as for men, age decreases the likelihood of binge drinking (0.826, $z = -33.83$) and White women are much less likely to engage in binge drinking than non-White women (0.338, $z = -3.59$).

Table B20 reports the likelihood that women either continue binge drinking, start binge drinking, or stop binge drinking relative to never having engaged in binge drinking over the period that runs from year $t - 2$ to year t. While men who lose breadwinner status are significantly more likely to continue binge drinking or stop binge drinking relative to never engaging in binge drinking (Table B15), losing breadwinner status does not affect the likelihood that women binge drink. However, while gaining breadwinner status does not affect the binge drinking habits of men, women who gain breadwinner status are much more likely to both either stop binge drinking (1.341, $z = 2.36$) or continue binge drinking (1.347, $z = 2.76$) relative to never having engaged in binge drinking. It is possible that engaging in binge drinking in year $t - 2$ paradoxically renders women more likely to gain breadwinner status, thereby increasing their likelihood of either continuing or stopping binge drinking in year t. Further, while losses of breadwinner status that coincide with losses of unemployment do not affect the likelihood that men binge drink, women who experience these dual losses are substantially more likely to stop binge drinking (3.380, $z = 1.73$). Among other potential explanations, it is possible that women who give up both their employment and primary earner obligations have more time to focus on moderating their drinking habits.

7 Discussion

In this paper, I explore the impacts of lacking and losing breadwinner status on the health of U.S. men. My results are largely inconclusive. Employed men who lose their breadwinner status are approximately 1.5 times more likely to indicate that their health has become "worse" than it was two years ago, relative to men who do not lose breadwinner status. Lacking breadwinner status leads employed men both to be nearly two times as likely to have serious mental illnesses as employed breadwinners and to have worse subjective health. Yet employed men who are not breadwinners are also significantly less likely to be obese relative to employed breadwinners, and men who lose breadwinner status are more likely to stop binge drinking than men who do not experience changes in breadwinner status. In general, while changes in breadwinner status affect the health of employed men, losses of breadwinner status that coincide with unemployment do not significantly impact men's health. Interestingly, I find that breadwinner status affects not only the health of men, but also that of women. However, while men who lose breadwinner status report that their health has worsened, women who lose breadwinner status are 1.3 times as likely to report "better" health relative to health that has remained the same over time.

These results suggest that gender norms may impact individual health outcomes in varying ways, rather than uniformly improving or harming health. While one might expect men who lose breadwinner status to suffer health consequences, given the social importance assigned to the male breadwinner role, my results indicate that men may experience positive benefits when they lose breadwinner status: they are less likely to engage in binge drinking. Men who are not breadwinners are also less likely to be obese. However, when asked to holistically compare their present health to their health prior to when they lost their breadwinner status, men who lose breadwinner status resoundingly indicate that their health has worsened. These findings invite myriad potential explanations. Men who lose breadwinner status may be correct in indicating that their overall health has declined, with their decreasing obesity constituting a sign of dysfunctional weight loss resulting from food insecurity. Alternatively, other aspects of men's health not explored here might have evolved in unfavorable ways as they lost their breadwinner status, aligning men's subjective appraisals of their health as declining with their objective health outcomes. Further research can more rigorously parse the relationships between men's subjective health, their objective health outcomes, and breadwinner status.

These findings conflict with my initial hypothesis: that losing or lacking breadwinner status will uniformly lead men to have worse health outcomes than they might have had if they had instead maintained breadwinner status. Previous research indicates that men who lose or lack breadwinner status are significantly more likely to have marital problems and decreased life satisfaction than men who are breadwinners (Bertrand et al., 2015; Folke and Rickne, 2020). In this paper, I hypothesized that these marital issues and this reduced life satisfaction would translate linearly into declines in physical and mental health for men who lack breadwinner status. In contrast, I find that lacking breadwinner status has mixed effects on the health of men: depending on the health outcome, lacking breadwinner status may reduce, improve, or have no effect on men's health. This result suggests that the relationship between breadwinner status, marital issues and reduced life satisfaction, and physical and mental health may be less straightforward than I hypothesized. Further research can clarify when and why breadwinner status and the relative incomes of partners may affect their health outcomes.

This paper cannot directly assess whether changes in men's health that occur after they lose breadwinner status are large enough to explain a significant portion of the recent uptick in "diseases of despair" among White men in the United States. However, findings point to a productive path forward for research on the causes of the rise in "diseases of despair" among these men. While previous research has located a distinct, yet largely unexplained, disparity in the prevalence of "diseases of despair" between White U.S. women and men, this paper proposes and conducts a preliminary test of a novel explanation for gender disparities in disease prevalence (Case and Deaton, 2017). My results indicate that gender norms that induce an aversion to situations in which women outearn their male partners may assist in explaining the prevalence of at least three "diseases of despair" among men—serious mental illness, binge drinking, and obesity—as well as declines in their general subjective well-being. These results provide preliminary support for the hypothesis that changes in breadwinner status may affect the prevalence of diseases of despair among men. Future research can clarify whether the effects of breadwinner status on health are unique to the White, working-class population that has seen most of the recent uptick in diseases of despair in the United States (Case and Deaton, 2017). It can also assess whether the magnitude of the impact of breadwinner status on health is sufficiently large to assist in explaining recent gender and racial disparities in the growth of diseases of despair.

Regardless of the direction of the effect of breadwinner status on health, in demonstrating that relative incomes within partnerships significantly affect health, this research assists in making the case for including a previously unexplored variable in research on the determinants of health of both U.S. men and women. Research has demonstrated that breadwinner status is a highly salient point of contention within married partnerships, impacting levels of marital discord and the probability that couples will divorce (Bertrand et al., 2015; Folke and Rickne, 2020). However, the effects of this stressor on the health and well-being of individuals is not well understood. My research provides a new path forward for the literature on the determinants of health within families, suggesting that gendered relative income norms may tangibly affect health. Gender norms surrounding breadwinner status may assist in explaining gender disparities in the prevalence of "diseases of despair," providing a new potential answer to the puzzle of unexplained recent upticks in these diseases.

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Appendix A: Data

Table A1: Lagging Independent and Dependent Variables for First Differences Model

This diagram illustrates the methods use to lag variables in the first differences model presented in subsection 5.2. In this model, differenced explanatory variables are lagged over different time spans than differenced outcome variables. Here, I provide an example of how this "alternating lags" differencing strategy plays out to render the logic behind the strategy more intuitive. Below, key explanatory variables, including breadwinner status and unemployment status, are differenced between years t and $t-1$. The interaction of the differenced breadwinner and unemployment variables is used to indicate whether an individual has "Lost breadwinner status" for plausibly exogenous reasons. The dependent variable, "Health," is differenced between years t and $t-2$. For illustrative purposes, the survey year 2007 provides an example of year t here.

	Year		
	2003	2005	2007
	$t-2$	$t-1$	t
Category	*Survey Year*		*Survey Year*
Breadwinner status	Breadwinner? $BS_{t-2} = 0, 1$	Breadwinner? $BS_{t-1} = 0, 1$	
	Breadwinner status change ($\Delta BS = BS_{t-1} - BS_{t-2} = -1, 0, 1$)		
Unemployment status	Unemployed? $UE_{t-2} = 0, 1$	Unemployed? $UE_{t-1} = 0, 1$	
	Unemployment status change ($\Delta UE = UE_{t-1} - UE_{t-2} = -1, 0, 1$)		
Breadwinner status × unemployment status			***Lost breadwinner status?*** (*Lost BS*$= 1$ *if* $\Delta BS = -1$ *and* $\Delta UE = 1$ *; else,* 0)
Health outcomes	Health (H_{t-1})		Health (H_t)
			Health status change ($\Delta H_t = H_t - H_{t-1}$)

Table A2: Variable Descriptions

This table describes the variables included in my analysis. Beyond the exclusions listed here, observations were excluded from analysis when data was reported unevenly across survey years. Responses to survey questions including "don't know," "not available," "inappropriate," and similar responses were also excluded for each variable. The survey years listed under "Availability" are the years for which data is available for each variable.

Notably, the PSID asks one adult in each family to answer survey questions on behalf of every individual in the family. This person may be either the "reference person," his or her spouse, or another member of the family unit. For this reason, "subjective well-being" is not "self-reported well-being," etc.

Variable	Name	Year	Description	Availability	Type
Key Independent Variables					
Log family income	*lnFamIncome*	Y_{t-1}	Natural log of the sum of the income of the male and female partners in a household. The incomes of each partner are artificially increased by $1 to avoid taking the natural log of zero for partners with no income. Couples are excluded from analysis in survey years in which any partner has a negative income or income that exceeds $999,999.00.	2001-2017	Continuous
Unemployment status	*Unemployed*	Y_{t-1}	"1" if an individual was unemployed at *any* point during a given year; "0" if the individual was *never* unemployed during that year.	2003-2017	Binary
Breadwinner status	*Breadwinner*	Y_{t-1}	"1" if an individual earned more than their spouse in a given year; "0" if an individual earned the same dollar amount or less than their spouse in a given year. Only calculated for individuals with spouses.	2001-2017	Binary

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Variable	Name	Year	Description	Availability	Type
Δ Log family income	$\Delta lnFamIncome$	$Y_{t-1} - Y_{t-2}$	Calculated as $lnFamIncome_{t-1} - lnFamIncome_{t-2}$.	2003-2017	Continuous
Δ Unemployment status	$\Delta Unemployed$	$Y_{t-1} - Y_{t-2}$	Based on the change in an individual's values of *Unemployed* between year $t-2$ and year $t-1$, individuals are sorted into two categories. "Became unemployed" includes only those individuals who were employed in year $t-2$ but became unemployed in year $t-1$, and all other individuals are designated as "Did not become unemployed."	2003-2017	Binary
Δ Breadwinner status	$\Delta Breadwinner$	$Y_{t-1} - Y_{t-2}$	Based on the change in an individual's values of *Breadwinner* between year $t-2$ and year $t-1$, individuals are sorted into three categories: "Lost" breadwinner status, "No change" in breadwinner status (maintained status as either breadwinner or non-breadwinner across both years), or "Gained" breadwinner status.	2003-2017	Categorical
Outcome Variables					
Serious mental illness	$Health_{it}$	Y_t	"1" (likely serious mental illness) if an individual has a K6 scale score of 13 or above; "0" (not likely serious mental illness) if an individual's score is below 13. See subsection 4.2.1 for further discussion.	2001-2003, 2007-2017	Binary

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Variable	Name	Year	Description	Availability	Type
"Good" subjective well-being	$Health_{it}$	Y_t	"1" ("good" subjective well-being) if an individual reports having "excellent," "very good," or "good" general health; "0" ("poor" subjective well-being) if an individual reports having either "fair" or "poor" health. See subsection 4.2.1 for further discussion.	2001-2017	Binary
Health better or worse	$Health_{it}$	Y_t	Indicates an individual's response to the question, "Compared to say, two years ago, would you say your health is better, about the same, or worse?" Responses may include "Better," "About the same," or "Worse."	2001-2017	Binary
Hypertension	$Health_{it}$	Y_t	"1" if an individual reports that his or her doctor has ever told him or her that he or she has high blood pressure or hypertension; "0" if not.	2001-2017	Binary
Obesity	$Health_{it}$	Y_t	"1" (obese) if an individual's BMI values fall within World Health Organization (2000) classifications for class I, class II, and class III obesity, which use BMI cutpoints of 30, 35, and 40, respectively; "0" if not. Observations are excluded for individual-year combinations in which individuals weigh ≤ 50 pounds or ≥ 400 pounds. See subsection 4.2.2 for further discussion.	2001-2017	Binary

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Variable	Name	Year	Description	Availability	Type
Binge drinking	$Health_{it}$	Y_t	"1" (engages in binge drinking) if a man reports having, "in the last year, on the days [he] drank," five or more drinks per day; "0" (does not engage in binge drinking) if four or fewer drinks, or if he does not drink. For women, "1" if four more drinks per day; "0" if three or fewer, or if they do not drink. See section 4.2.2 for further discussion.	2001-2017	Binary
Δ Serious mental illness	$Health_{it}$	$Y_t - Y_{t-2}$	Based on the change in their values of "Serious Mental Illness" between years $t-2$ and $t-1$, individuals are sorted into four categories: "Stayed likely" includes those individuals whose K6 scores indicate that they likely had a serious mental illness (SMI) in both year $t-2$ and year t; "stayed unlikely" includes individuals whose scores indicated that they were unlikely to have SMIs throughout the time period; "improved" includes those who become less likely to have an SMI over this time period; and "declined" includes those who became more likely to have an SMI during this time period.	2003, 2005-2017	Categorical

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Variable	Name	Year	Description	Availability	Type
Δ "Good" subjective well-being	$Health_{it}$	$Y_t - Y_{t-2}$	Based on the change in their values of "'Good' Subjective Well-being" between years $t-2$ and $t-1$, individuals are sorted into four categories. Individuals are designated as having health that "stayed good" if their subjective well-being was "good" in both years; health that "stayed poor" if they had "poor" subjective well-being in both years; or health that "improved" or "declined."	2001-2017	Categorical
Δ Hypertension	$Health_{it}$	$Y_t - Y_{t-2}$	Based on the change in their values of "Hypertension" between years $t-2$ and $t-1$, individuals are sorted into four categories. Individuals are designated as having "maintained hypertension" if they had hypertension during both years; "never had hypertension" if they did not indicate having hypertension during either year; "no longer" have hypertension if they had hypertension in year $t-2$ but not in year t; and "developed" if they developed hypertension over the course of the study period.	2001-2017	Categorical

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Variable	Name	Year	Description	Availability	Type
Δ Obesity	$Health_{it}$	$Y_t - Y_{t-2}$	Based on the change in their values of "Obesity" between years $t-2$ and $t-1$, individuals are sorted into four categories: "Stayed obese" if they were obese during both survey years; "never obese" if their BMI was below the cutpoints for obesit during both years; "no longer obese" if they were initially obese but then returned to a non-obese BMI; and "became obese" if they became obese during the course of the study period.	2001-2017	Categorical
Δ Binge drinking	$Health_{it}$	$Y_t - Y_{t-2}$	Based on the change in their values of "Binge Drinking" between years $t-2$ and $t-1$, individuals are sorted into four categories: "Continued binging" if they engaged in binge drinking during both study years; "never binged" if they did not binge drink during either study year; "stopped binging" if they binge drank during year $t-2$ but not in year t; and "started binging" if they did not binge drink in year $t-2$ but did in year t.	2001-2017	Categorical
Control Variables					
Age, year $t-2$	$\mathbf{Y}'_{it-2}$	Y_{t-2}	The age of individuals in number of years. Observations are excluded for individuals less than 18 or greater than 65 years old.	2001-2017	Continuous
Black	$\mathbf{X}'_i$	Y_t	"1" if an individual reports his or her race as "Black"; "0" if not. Reference individuals may report on behalf of their spouses.	2001-2017	Binary
White	$\mathbf{X}'_i$	Y_t	"1" if an individual reports his or her race as "White"; "0" if not. Reference individuals may report on behalf of their spouses.	2001-2017	Binary

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Variable	Name	Year	Description	Availability	Type
16+ years of education	$\mathbf{Y}'_{it-2}$	Y_{t-2}	"1" if an individual completed 16 or more years of education; "0" if an individual completed less than 16 years of education. For many individuals, 16 years of education corresponds to 12 years of grade school and four years of college; however, this may not be true for all students.	2001-2017	Binary
Child 17 or younger	$\mathbf{Y}'_{it-2}$	Y_{t-2}	"1" if there is a child 17 years or younger in the family unit; "0" if not.	2001-2017	Binary
Region	$\mathbf{Y}'_{it-2}$	Y_{t-2}	Indicates the region of interview, i.e., the region in which the survey respondent (typically the reference person) lived at the time of interview. Since there is no variable that indicates where the spouse or other partner currently lives, I assume that both partners live in the same region. Regions include the "Northeast," which includes the states CT, ME, MA, NH, NJ, NY, PA, RI, and VT; "North Central," which includes the states IL, IN, IA, IN, KS, MI, MN, MO, NE, ND, OH, SD, and WI; "South," which includes AL, AR, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV, and Washington, D.C.; and "West," which includes AZ, CA, CO, ID, MT, NV, NM, OR, UT, WA, and WY. Observations for couples who live in Alaska, Hawaii, and countries other than the United States were excluded due to low numbers of observations.	2001-2017	Binary

Table A3: Interpreting Model Coefficients with Interaction Term

These tables describe how to interpret model coefficients for the pooled logistic regression, fixed effects, and random effects models. The inclusion of an interaction term in these models alters the interpretation of variables representing unemployment and breadwinner status. Interpreting these coefficients when results are reported as odds ratios can be complicated. Here, I develop two simple tables to describe how to generatively interpret these model coefficients.

Variable Name	**Coefficient**	**Interpretation of Exponentiated Coefficient**
Unemployed	UE	Odds ratio
Not Breadwinner	Not BW	Odds ratio
Unemployed × Not Breadwinner	(UE # Not BW)	Ratio of odds ratios
[Continuous variables]		Odds ratio
Constant		Baseline odds

Interpretation	**UE**	**Not BW**	**Odds Ratio**	**Coefficient Math**
Likelihood of having health outcome for...				
Unemployed breadwinners relative to employed breadwinners	1: 0	0	OR for Unemployed: Employed when Not Breadwinner = 0	UE
Unemployed non-breadwinners relative to employed non-breadwinners	1: 0	1	OR for Unemployed: Employed when Breadwinner = 1	UE ∗ (UE # Not BW)
Employed non-breadwinners relative to employed breadwinners	0	1: 0	OR for Not Breadwinner: Breadwinner when Unemployed = 0	Not BW
Unemployed non-breadwinners relative to unemployed breadwinners	1	1: 0	OR for Not Breadwinner: Breadwinner when Unemployed = 1	Not BW ∗ (UE # Not BW)
Interpretation for interaction effects				
Extent to which being unemployed increases your odds of having health outcome, for non-breadwinners relative to breadwinners			OR for (Unemployed: Employed if not breadwinner)/(Unemployed: Employed if breadwinner)	UE # Not BW
Extent to which not being breadwinner increases your odds of having health outcome, for unemployed relative to employed individuals			OR for (Not Breadwinner: Breadwinner if unemployed)/(Not Breadwinner: Breadwinner if employed)	UE # Not BW

Tables A4-A5: Unemployment as an Exogenous Shock to Breadwinner Status

This paper seeks to understand the impact of changes in breadwinner status on the health of men, regardless of the cause of fluctuations in relative incomes within couples. However, men who experience *exogenous* shocks to their breadwinner status may experience more severe adverse health impacts. For example, while men who choose to give up breadwinner status to take care of a family member may experience a lifted mood or other positive benefits when they take on a new, valued social role, men who unexpectedly lose breadwinner status as a result of events that they cannot control may find this change in status distressing. In subsection 4.1, I introduce the strategy of leveraging unemployment as an exogenous shock to breadwinner status to determine how changes in breadwinner status affect health. Unemployment events are excellent candidates for plausibly exogenous shocks to breadwinner status: they are often both unwanted and unexpected, and they frequently result in significant income losses for individuals. However, unemployment may not always be exogenous, and it may not always affect breadwinner status.

Below, I argue that although unemployment events may imperfectly correlate with breadwinner status losses, they indeed constitute suitable, plausibly exogenous shocks to breadwinner status. The discussion below refers most directly to the interactions between unemployment status variables and breadwinner status variables reported in Tables B8 through B15. In each of these tables, interaction terms, "Unemployed × Not Breadwinner" or "Became Unemployed × Lost" breadwinner status are taken as indicators that men have experienced plausibly exogenous, unemployment-induced losses of breadwinner status. Here, I briefly report the reasons for selecting unemployment as a shock to breadwinner status, and I describe the nuances involved in discerning to what extent unemployment events indeed constitute exogenous shocks to breadwinner status in the data.

Selection of Unemployment as a Shock to Breadwinner Status

Unemployment events are not uniformly exogenous to health, and scholars interested in examining the effects of shocks to breadwinner status on men's health may instead consider studying alternative shocks, such as wives' unexpected salary raises. However, if not perfectly exogenous to health, unemployment may be more exogenous than other potential shocks to breadwinner status. Below, I briefly elaborate on the challenges and benefits of leveraging unemployment as a shock to breadwinner status, observing that this shock may have advantages over others.

First, despite the typically unwanted and unexpected character of unemployment, employment events are *not* always exogenous to health. Health may affect both whether a person becomes unemployed and whether he loses his breadwinner status, regressions of health on unemployment suffer from potential reverse causality concerns. In this paper, I seek to avoid these concerns by examining the effects of changes in unemployment status between years t and $t-1$ on health in year 2. By examining the impact of *lagged* breadwinner status changes on health, I avoid potential simultaneity issues that might occur if both health and breadwinner status change simultaneously as the result of changes in an omitted variable. Notably, however, even lagged unemployment events may not always be exogenous to health. Men may become unemployed in part because of an unobserved variable, such as an underlying and gradually worsening illness, that both render them unable to perform adequately at work, inducing their bosses to fire them, and adversely impact their health a year later. These concerns are important, and they attenuate my findings regarding the effects of unemployment-induced breadwinner status losses on health.

However, there are reasons to expect that endogeneity issues may be *more* severe for alternative shocks to breadwinner status than for unemployment. Men may also lose breadwinner status if their wives are promoted at work, if they negotiate to move toward a part-time rather than a full-time schedule so that they can care for a child, or for other reasons. Yet these shocks often involve a greater choice component than unemployment, increasing the severity of selection concerns. For example, U.S. women are less likely to take positions that lead them to outearn their husbands, suggesting that that couples in which wives take promotions that might lead them to outearn their husbands might have more egalitarian, amicable, or supportive partnerships than those who do not (Bertrand et al., 2015). Men in these unusually egalitarian partnerships may be less likely to experience adverse health effects if they lose breadwinner status than other men, and it may be difficult to disentangle the health effects of an unobserved "marital egalitarianism" from those of breadwinner status loss. Further, while couples who choose to support a female partner in taking a promotion or a male partner in moving to part-time work to care for a child are effectively making a decision as to whether or not the male partner loses breadwinner status, unemployment events may be experienced as undesirable or unexpected shocks. Compared to alternative shocks to breadwinner status, unemployment is presumably less likely to result from a *choice* made by partners, relieving the analysis of a potential selection issue. Unemployment represents a strong and plausibly exogenous shock to men's breadwinner status, even if it is imperfect.

Endogeneity Issues with PSID Data

The structure of the PSID data introduces additional endogeneity concerns to the analysis of the impact of unemployment-induced losses of breadwinner status on health. Fortunately, an overview of the statistical relationship between changes in unemployment and changes in breadwinner status suggests that these concerns do not imperil the analysis.

First, this paper aims to assess the impact of unemployment-induced losses of breadwinner status on men's health. However, PSID data render it difficult to discern which specific changes in employment status coincide with changes in men's breadwinner status. While PSID data on men's unemployment status is available on a weekly basis for years $t-2$ and $t-1$, the years over which change in men's breadwinner status is calculated, complete data on labor incomes is available only on an annual basis during this time period. Given that many events–raises, work hours changes, changes in wife's incomes, and other changes–may lead to fluctuations in whether a given partner possesses primary breadwinner status over the course of a full year, it is difficult to ascertain whether a given change in one partner's employment status directly coincides with changes in his breadwinner status. For this reason, even if a man becomes unemployed and loses breadwinner status during a given year, he may not have lost breadwinner status *as a result* of his loss of employment. Accordingly, simplifying assumptions are instead needed to clarify whether men's breadwinner status losses likely resulted from unemployment, as opposed to another cause.

In my first differences analyses, I assume that men's losses of breadwinner status resulted from their unemployment when they "Became Unemployed" and "Lost breadwinner status" during the same time period. The interaction of these two variables, "Became Unemployed $\times$ Lost" breadwinner status, is taken as a signal that men have experienced unemployment-induced losses of breadwinner status. In the data, men are designated as having jointly "Became Unemployed" and "Lost" breadwinner status if they satisfy three criteria: (1) they lost their status as primary breadwinner between years $t-2$ and $t-1$, (2) they were *never* unemployed during year $t-2$, and (3) they became unemployed for at least some interval of time during year $t-1$. The question remains: is this a fair set of criteria for assuming that men have lost breadwinner status as a *result* of unemployment?

The data suggest that these criteria are indeed a strong indicator of whether or not men have experienced unemployment-induced losses of breadwinner status (Tables A4 and A5). First, one might expect that *most* men who become unemployed *do* lose breadwinner status as a result of their unemployment, even though some unemployed men may maintain or gain status as breadwinner if their partners also experience unemployment or if they later land a higher-paying job, etc. Table A4 indicates that this is indeed the case: men who experienced this employment transition, or men who "Became unemployed," are more than twice as likely to lose breadwinner status than to gain it. Second, one might expect that those men who lose breadwinner status as a result of unemployment typically experience longer unemployment spells than men who become unemployed but are still able to maintain their status as breadwinner. This assumption finds validation in Table A5, which indicates that men who become unemployed and lose breadwinner status are typically unemployed for 13.83 weeks, while men who gain breadwinner status despite unemployment are only unemployed for 9.12 weeks.

Table A4: Frequency Table, Change in Employment Status and Change in Breadwinner Status, Year $t-2$ to $t-1$

	Δ Breadwinner Status			
Δ Employment Status	No Change	Lost	Gained	Total
Became unemployed	411	101	39	551
Never unemployed	13,838	1,094	784	15,716
Consistently unemploy	278	58	37	373
No longer unemployed	462	34	98	594
Total	14,989	1,287	958	17,234

Note: $N = 17,234$ individual-year observations for year t for the first differences model. This is the full sample of observations from which the samples for each first differences model was pulled. The actual sample sizes for the first differences models were smaller, given that the outcome variables actually used in each model may not have been available for every man in the complete sample.

Table A5: Mean Change in Number of Weeks Unemployed Between Years $t-2$ and $t-1$, By Change in Employment and Change in Breadwinner Status

	Δ Breadwinner Status		
Δ Employment Status	No Change	Lost	Gained
Became unemployed	13.83	21.59	9.12
Never unemployed	0.00	0.00	0.00
Consistently unemployed	4.34	13.02	-8.12
No longer unemployed	-14.53	-13.16	-19.04

Note: This table reports the mean change in the annual number of weeks that men reported being unemployed between years $t-2$ and $t-1$. Men may report being unemployed for 0 to 52 weeks each year. For each man, the change in weeks unemployed from year to year may range from -52 to 52.

These results suggest that although changes in employment status that occur over the course of a year may not constitute perfect instruments for assessing whether or not losses of breadwinner status *result* from unemployment, they do typically affect breadwinner status.

Strict Exogeneity Assumption

This paper includes both fixed effects and first differences models as primary specifications. However, the choice *between* first differences and fixed effects models typically hinges on whether the researcher believes that the strict exogeneity assumption for the fixed effects approach holds. For the fixed effects model, the strict exogeneity assumption is that $E(u_{it} - \bar{u}_{it}|x_{it} - \bar{x}_{it}) = E(u_{it} - \bar{u}_{it}) = 0$ for all explanatory variables x_{it}, where u_{it} is idiosyncratic or time-varying error. For the coefficients in fixed effects estimation to be unbiased, all explanatory variables must be strictly exogenous after removing the unobserved or fixed effect. The relevant assumption is slightly different for the first differences approach: $E(u_{it} - u_{it-1}|x_{it} - x_{it-1}) = E(u_{it} - u_{it-1}) = 0$. This assumption is a weaker form of strict exogeneity than that required for fixed effects: for example, the assumption that x_{it} is uncorrelated with u_{it-2} is not required. However, the fixed effects approach is generally less biased than the first differences approach if each x_{it} *is* uncorrelated with u_{it}, but the strict exogeneity assumption is otherwise violated (e.g., because there is correlation between u_{it} and x_{it+1}) (Wooldridge, 2012). For this reason, a fixed effects approach is generally preferred to the first differences approach so long as strict exogeneity assumption for fixed effects holds.

Which assumption is warranted in this case? If there is feedback between u_{it} and x_{it} that spans more than two periods (i.e., x_{it} is correlated with u_{it-2}, u_{it-3}, or u_{it-4}, etc.), a first differences model will be consistent when a fixed effects model is not. There may exist some of this feedback in my model, but it is unclear. For example, an unusually harsh influenza season in year $t - 3$ may affect both health in year t and the likelihood that a person is breadwinner in year $t - 1$, if the flu has lasting health effects on the health of individuals with pre-existing conditions and also harms their ability to perform at work and earn a high salary. However, this example is somewhat far-fetched, and I do not expect that this feedback is sufficiently severe as to violate the strict exogeneity assumption for fixed effects. For this reason, I include the fixed effects approach as a primary specification in my paper.

The choice to include a first differences approach *alongside* the fixed effects approach as a second primary specification is somewhat unorthodox. However, as discussed in section 5.2, the first differences approach allows me to examine the impact of immediate *losses* of breadwinner status on health, a slightly different task than that accomplished by the fixed effects model, which instead examines the impact of general variation in breadwinner status over time on health. As I only examine these losses with a first differences model in this paper and feel that they are integral to the main discussion of the impact of breadwinner status on health, I include the first differences model as a primary specification here. (In a future paper, it would be interesting to examine the impact of these losses on health with a fixed effects approach as well.) My present empirical strategy limits the analysis of "change" outcome variables to the first differences approach, so I also examine the impact of changes in breadwinner status on changes in whether or not individuals report that their health had improved or declined during this period using a first differences approach but not a fixed effects approach (Table B11). As I feel that this result is critical to understanding the impact of breadwinner status on health, it is important to me to include the first differences model as a primary empirical specification here.

Appendix B: Tables

Table B1: Summary Statistics for Serious Mental Illness, Men

	Logit and RE	Fixed Effects
	Mean (SD)	Mean (SD)
Serious Mental Illness, t	0.02	0.32
	(0.13)	(0.47)
Log Family Income, $t-1$	10.62	9.76
	(2.42)	(3.07)
Total Family Income, $t-1$	\$87,291.13	\$55,725.00
	(\$80,499.91)	(\$55,216.61)
Whether Unemployed, $t-1$	0.08	0.15
	(0.27)	(0.35)
Male Primary Breadwinner, $t-1$	0.69	0.52
	(0.46)	(0.5)
Age, $t-2$	42.12	40.31
	(11.79)	(11.35)
Has Child 17 Years or Younger, $t-2$	0.5	0.59
	(0.5)	(0.49)
Whether 16+ Years of Education, $t-2$	0.36	0.17
	(0.48)	(0.38)
Black	0.22	0.36
	(0.41)	(0.48)
White	0.72	0.58
	(0.45)	(0.49)
Observations	10,516	413

Table B2: Summary Statistics for "Good" Subjective Health, Men

	Logit and RE	Fixed Effects	First Differences
	Mean	Mean	Mean
	(SD)	(SD)	(SD)
"Good" Subjective Health, t	0.89	0.64	0.92
	(0.32)	(0.48)	(0.27)
"Good" Subjective Health, $t-2$			0.94
			(0.25)
Log Family Income, $t-1$	10.6	10.05	11.2
	(2.33)	(2.78)	(1.03)
Total Family Income, $t-1$	$80,859.97	$59,491.55	$94,477.65
	($71,526.83)	($51,766.06)	($68,112.47)
Whether Unemployed, $t-1$	0.07	0.1	0.05
	(0.25)	(0.3)	(0.23)
Male Primary Breadwinner, $t-1$	0.68	0.61	0.68
	(0.47)	(0.49)	(0.46)
Age, $t-2$	42.17	44.89	41.27
	(11.34)	(10.75)	(10.81)
Has Child 17 Years or Younger, $t-2$	0.56	0.55	0.56
	(0.5)	(0.5)	(0.5)
Whether 16+ Years of Education, $t-2$	0.3	0.17	0.34
	(0.46)	(0.37)	(0.47)
Black	0.23	0.31	0.2
	(0.42)	(0.46)	(0.4)
White	0.7	0.6	0.75
	(0.46)	(0.49)	(0.44)
Observations	26,870	6,056	17,216

Table B3: Summary Statistics for Hypertension, Men

	Logit and RE	Fixed Effects
	Mean	Mean
	(SD)	(SD)
Hypertension, t	0.27	0.46
	(0.44)	(0.5)
Log Family Income, $t-1$	10.6	10.49
	(2.33)	(2.47)
Total Family Income, $t-1$	\$80,859.55	\$76,940.71
	(\$71,535.14)	(\$65,391.68)
Whether Unemployed, $t-1$	0.07	0.07
	(0.25)	(0.26)
Male Primary Breadwinner, $t-1$	0.68	0.67
	(0.47)	(0.47)
Age, $t-2$	42.17	44.21
	(11.34)	(10.65)
Has Child 17 Years or Younger, $t-2$	0.56	0.56
	(0.5)	(0.5)
Whether 16+ Years of Education, $t-2$	0.3	0.26
	(0.46)	(0.44)
Black	0.23	0.25
	(0.42)	(0.43)
White	0.7	0.68
	(0.46)	(0.47)
Observations	26,861	7,891

Table B4: Summary Statistics for Obesity, Men

	Logit and RE	Fixed Effects
	Mean	Mean
	(SD)	(SD)
Obese, t	0.33	0.49
	(0.47)	(0.5)
Log Family Income, $t-1$	10.6	10.58
	(2.33)	(2.23)
Total Family Income, $t-1$	$80,827.47	$75,863.11
	($71,510.29)	($65,170.07)
Whether Unemployed, $t-1$	0.07	0.07
	(0.25)	(0.26)
Male Primary Breadwinner, $t-1$	0.68	0.69
	(0.47)	(0.46)
Age, $t-2$	42.17	42.72
	(11.34)	(10.62)
Has Child 17 Years or Younger, $t-2$	0.56	0.6
	(0.5)	(0.49)
Whether 16+ Years of Education, $t-2$	0.3	0.24
	(0.46)	(0.43)
Black	0.23	0.26
	(0.42)	(0.44)
White	0.7	0.66
	(0.46)	(0.47)
Observations	26,904	7,746

Table B5: Summary Statistics for Binge Drinking, Men

	Logit and RE	Fixed Effects	First Differences
	Mean	Mean	Mean
	(SD)	(SD)	(SD)
Binge Drinking, t	0.46	0.38	0.42
	(0.5)	(0.48)	(0.49)
Binge Drinking, $t-2$			0.5
			(0.5)
Log Family Income, $t-1$	10.6	10.68	11.2
	(2.33)	(2.25)	(1.03)
Total Family Income, $t-1$	$80,827.47	$84,741.19	$94,445.51
	($71,510.29)	($73,543.26)	($68,098.12)
Whether Unemployed, $t-1$	0.07	0.06	0.05
	(0.25)	(0.24)	(0.23)
Male Primary Breadwinner, $t-1$	0.68	0.69	0.68
	(0.47)	(0.46)	(0.46)
Age, $t-2$	42.17	43.36	41.27
	(11.34)	(10.91)	(10.81)
Has Child 17 Years or Younger, $t-2$	0.56	0.57	0.56
	(0.5)	(0.5)	(0.5)
Whether 16+ Years of Education, $t-2$	0.3	0.31	0.34
	(0.46)	(0.46)	(0.47)
Black	0.23	0.21	0.2
	(0.42)	(0.41)	(0.4)
White	0.7	0.73	0.75
	(0.46)	(0.44)	(0.44)
Observations	26,904	16,889	17,234

Table B6: Summary Statistics for Health Better or Worse than Two Years Ago, Men

	First Differences
	Mean (SD)
Log Family Income, $t-1$	11.2 (1.03)
Total Family Income, $t-1$	\$94,457.88 (\$68,103.40)
Whether Unemployed, $t-1$	0.05 (0.23)
Male Primary Breadwinner, $t-1$	0.68 (0.46)
Age, $t-2$	41.27 (10.81)
Has Child 17 Years or Younger, $t-2$	0.56 (0.5)
Whether 16+ Years of Education, $t-2$	0.34 (0.47)
Black	0.2 (0.4)
White	0.75 (0.44)
Observations	17,229

Table B7: Summary Statistics for First Differences Models, Men

	Δ Breadwinner Status			
	No Change	Lost	Gained	Total
Δ *Good Subjective Health*				
Stayed Good	13,373	1,101	855	15,329
Stayed Poor	484	59	27	570
Improved	461	52	30	543
Declined	657	71	46	774
Total	14,975	1,283	958	17,216
Δ *Binge Drinking*				
Never Binge Drank	6,461	514	408	7,383
Continued Binging	5,348	503	306	6,157
Started Binging	989	80	90	1,159
Stopped Binging	2,191	190	154	2,535
Total	14,989	1,287	958	17,234
Health Better or Worse Than Two Years Ago				
About the Same	11,586	950	709	13,245
Better	1,997	155	155	2,307
Worse	1,404	180	93	1,677
Total	14,987	1,285	957	17,229

Note: This two-way frequency table reports the number of observations for men who experienced each of the changes in health outcomes and changes in breadwinner status examined in the first differences models. The observations are categorized based on the changes in health outcomes (see left column) and the changes in breadwinner status ("no change," "lost," or "gained") that men experienced between years t and $t-2$. The frequencies reported here are the frequencies of individual-year t observations for men who fell within each health/breadwinner category. Men who appear in the dataset over multiple years t may be counted more than once in this table.

Table B8: Impact of Breadwinner Status on Prevalence of Serious Mental Illness, Men

VARIABLES	(1) Logit	(2) Fixed Effects	(3) Random Effects
Log Family Income, $t-1$	0.918***	0.877	0.879***
	(0.0220)	(0.0766)	(0.0290)
Unemployed, $t-1$	1.675	0.498	1.280
	(0.700)	(0.320)	(0.717)
Not Breadwinner, $t-1$	2.297***	1.977*	2.783***
	(0.496)	(0.803)	(0.755)
Unemployed $\times$ Not Breadwinner, $t-1$	0.877	1.645	1.003
	(0.410)	(1.212)	(0.657)
Age, $t-2$	0.972***	0.959	0.956***
	(0.00749)	(0.0310)	(0.0104)
Has Child 17 Years or Younger, $t-2$	1.006	0.524*	0.866
	(0.193)	(0.181)	(0.208)
Whether 16+ Years of Education, $t-2$	0.412***	0.783	0.285***
	(0.119)	(0.712)	(0.0962)
Black	1.623		1.735
	(0.749)		(1.060)
White	1.142	2.244e+06	1.213
	(0.513)	(4.382e+09)	(0.705)
Region, Northeast, $t-2$	1.106	3.141e+07	1.090
	(0.345)	(1.183e+11)	(0.462)
Region, North Central, $t-2$	0.908	1.784e+14	0.945
	(0.235)	(7.883e+17)	(0.324)
Region, West, $t-2$	0.790	6.806e+07	0.814
	(0.220)	(3.676e+11)	(0.309)
Constant	0.0836***		0.0189***
	(0.0549)		(0.0171)
Observations	10,516	413	10,516
Number of unique individuals		96	3,111

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios. Models (1) and (2) include clustering at the individual level.

Table B9: Impact of Breadwinner Status on Prevalence of "Good" Subjective Health Rating, Men

VARIABLES	(1) Logit	(2) Fixed Effects	(3) Random Effects
Log Family Income, $t-1$	1.116***	1.022	1.115***
	(0.0104)	(0.0162)	(0.0157)
Unemployed, $t-1$	0.506***	0.792	0.559***
	(0.0535)	(0.124)	(0.0882)
Not Breadwinner, $t-1$	0.587***	0.773***	0.589***
	(0.0373)	(0.0757)	(0.0510)
Unemployed $\times$ Not Breadwinner, $t-1$	1.728***	1.340	1.766***
	(0.255)	(0.282)	(0.383)
Age, $t-2$	0.962***	0.892***	0.928***
	(0.00286)	(0.00740)	(0.00446)
Has Child 17 Years or Younger, $t-2$	0.902	0.883	0.896
	(0.0569)	(0.0892)	(0.0748)
Whether 16+ Years of Education, $t-2$	2.741***	1.049	4.410***
	(0.254)	(0.252)	(0.630)
Black	1.464***	0.346	0.907
	(0.199)	(0.486)	(0.184)
White	1.935***	0.879	2.016***
	(0.243)	(0.265)	(0.371)
Region, Northeast, $t-2$	1.202	0.278**	1.081
	(0.137)	(0.167)	(0.186)
Region, North Central, $t-2$	1.097	0.780	1.005
	(0.0963)	(0.366)	(0.132)
Region, West, $t-2$	1.108	0.748	1.061
	(0.110)	(0.356)	(0.156)
Constant	8.158***		220.7***
	(1.869)		(81.69)
Observations	26,870	6,056	26,870
Number of unique individuals		1,091	6,364

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios. Models (1) and (2) include clustering at the individual level.

Table B10: Impact of Breadwinner Status on Change in "Good" Subjective Health Rating, Men

	Stayed Poor	Improved	Declined
VARIABLES	(1)	(2)	(3)
Δ Log Family Income	1.055	1.049	0.981
	(0.0755)	(0.078)	(0.0589)
Δ Unemployment Status			
Became Unemployed	2.068**	1.547	2.234***
	(0.646)	(0.512)	(0.629)
Δ Breadwinner Status			
Lost	1.348	1.3	1.149
	(0.283)	(0.277)	(0.228)
Gained	0.792	0.811	0.906
	(0.211)	(0.21)	(0.211)
Δ Unemployment × Δ Breadwinner			
Became Unemployed × Lost	0.842	0.671	0.744
	(0.576)	(0.511)	(0.482)
Became Unemployed × Gained	0.291	0.34	0.321
	(0.369)	(0.425)	(0.323)
Age, $t-2$	1.116***	1.086***	1.094***
	-(0.00913)	-(0.00877)	-(0.00847)
Has Child 17 or Younger, $t-2$	1.273*	1.208	1.231
	(0.177)	(0.168)	(0.16)
Whether 16+ Years of Education, $t-2$	0.166***	0.211***	0.198***
	(0.0334)	(0.0423)	(0.0379)
Black	0.885	1.643	1.468
	(0.313)	(0.593)	(0.507)
White	0.579*	0.728	0.68
	(0.178)	(0.232)	(0.206)
Region, Northeast, $t-2$	0.751	0.772	0.77
	(0.197)	(0.204)	(0.194)
Region, North Central, $t-2$	0.924	0.995	1.017
	(0.198)	(0.213)	(0.208)
Region, West, $t-2$	0.784	0.771	0.728
	(0.19)	(0.189)	(0.171)
Constant	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Observations	17,216	17,216	17,216

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. This table reports odds ratios for the likelihood that an individual's subjective health status would remain "fair" or "poor" between years $t-2$ and t ("Stayed Poor"), become at least "good" from "fair" or "poor" during this period ("Improved"), or become "fair" or "poor" from "good" during this period ("Declined"), relative to the odds that he would maintain "good" or better health throughout the period.

Table B11: Impact of Breadwinner Status on Whether Health Better or Worse Than Two Years Ago, Men

	Better	Worse
VARIABLES	(1)	(2)
Δ Log Family Income	0.951	0.96
	(0.0294)	(0.029)
Δ Unemployment Status		
Became Unemployed	1.267	1.681***
	(0.197)	(0.284)
Δ Breadwinner Status		
Lost	0.956	1.474***
	(0.103)	(0.155)
Gained	1.121	1.162
	(0.121)	(0.148)
Δ Unemployment $\times$ Δ Breadwinner		
Became Unemployed $\times$ Lost	0.948	0.69
	(0.355)	(0.263)
Became Unemployed $\times$ Gained	1.127	0.565
	(0.532)	(0.389)
Age, $t-2$	0.983***	1.024***
	(0.0027)	(0.00316)
Has Child 17 or Younger, $t-2$	0.857***	0.967
	(0.0479)	(0.0616)
Whether 16+ Years of Education, $t-2$	1.062	0.742***
	(0.068)	(0.0532)
Black	1.101	0.594***
	(0.156)	(0.0953)
White	0.83	0.942
	(0.106)	(0.131)
Region, Northeast, $t-2$	1.213**	1.091
	(0.113)	(0.111)
Region, North Central, $t-2$	0.963	0.961
	(0.0758)	(0.0828)
Region, West, $t-2$	1.113	1.016
	(0.0958)	(0.0962)
Constant	3.392***	3.392***
	(0.300)	(0.300)
Observations	17,229	17,229

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios.

Table B12: Impact of Breadwinner Status on Hypertension Status, Men

VARIABLES	(1) Logit	(2) Fixed Effects	(3) Random Effects
Log Family Income, $t-1$	0.964***	0.956**	0.940***
	(0.00916)	(0.0176)	(0.0166)
Unemployed, $t-1$	1.310***	1.153	1.275
	(0.124)	(0.197)	(0.209)
Not Breadwinner, $t-1$	1.168***	1.051	1.189*
	(0.0634)	(0.103)	(0.107)
Unemployed × Not Breadwinner, $t-1$	0.682***	0.807	0.695
	(0.0898)	(0.186)	(0.158)
Age, $t-2$	1.068***	1.295***	1.243***
	(0.00267)	(0.0110)	(0.00957)
Has Child 17 Years or Younger, $t-2$	0.923	0.951	0.912
	(0.0464)	(0.0895)	(0.0822)
Whether 16+ Years of Education, $t-2$	0.810***	0.712	0.570***
	(0.0530)	(0.166)	(0.0827)
Black	1.541***	614,683	4.008***
	(0.202)	(4.604e+08)	(1.040)
White	1.121	1.533	1.552*
	(0.134)	(0.706)	(0.354)
Region, Northeast, $t-2$	0.921	0.979	0.766
	(0.0851)	(0.414)	(0.142)
Region, North Central, $t-2$	0.794***	0.879	0.597***
	(0.0610)	(0.360)	(0.0957)
Region, West, $t-2$	0.758***	1.432	0.607***
	(0.0635)	(0.596)	(0.107)
Constant	0.0290***		4.90e-06***
	(0.00597)		(2.55e-06)
Observations	26,861	7,891	26,861
Number of unique individuals		1,373	6,363

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios. Models (1) and (2) include clustering at the individual level.

Table B13: Impact of Breadwinner Status on Prevalence of Obesity, Men

VARIABLES	(1) Logit	(2) Fixed Effects	(3) Random Effects
Log Family Income, $t-1$	0.978**	0.982	0.974
	(0.00914)	(0.0171)	(0.0166)
Unemployed, $t-1$	1.121	1.204	1.309*
	(0.0900)	(0.189)	(0.207)
Not Breadwinner, $t-1$	0.872***	0.773***	0.788***
	(0.0433)	(0.0685)	(0.0680)
Unemployed $\times$ Not Breadwinner, $t-1$	0.970	0.838	0.811
	(0.107)	(0.181)	(0.175)
Age, $t-2$	1.001	1.106***	1.057***
	(0.00218)	(0.00759)	(0.00579)
Has Child 17 Years or Younger, $t-2$	1.092*	1.121	1.194**
	(0.0491)	(0.0915)	(0.0986)
Whether 16+ Years of Education, $t-2$	0.599***	0.981	0.424***
	(0.0372)	(0.190)	(0.0594)
Black	1.394***	0.375	3.370***
	(0.163)	(0.339)	(0.910)
White	1.087	0.902	1.105
	(0.115)	(0.253)	(0.223)
Region, Northeast, $t-2$	0.964	1.508	0.846
	(0.0823)	(0.726)	(0.170)
Region, North Central, $t-2$	0.975	1.044	0.960
	(0.0667)	(0.358)	(0.153)
Region, West, $t-2$	0.897	1.051	0.740*
	(0.0688)	(0.443)	(0.129)
Constant	0.599***		0.00735***
	(0.110)		(0.00318)
Observations	26,904	7,746	26,904
Number of unique individuals		1,365	6,368

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios. Models (1) and (2) include clustering at the individual level.

Table B14: Impact of Breadwinner Status on Prevalence of Binge Drinking, Men

VARIABLES	(1) Logit	(2) Fixed Effects	(3) Random Effects
Log Family Income, $t-1$	0.916***	0.987	0.925***
	(0.00770)	(0.0128)	(0.00998)
Unemployed, $t-1$	0.976	0.840	0.893
	(0.0757)	(0.0989)	(0.0934)
Not Breadwinner, $t-1$	0.875***	1.241***	0.953
	(0.0356)	(0.0790)	(0.0501)
Unemployed $\times$ Not Breadwinner, $t-1$	1.051	0.995	0.973
	(0.112)	(0.162)	(0.140)
Age, $t-2$	1.006***	0.829***	0.980***
	(0.00182)	(0.00438)	(0.00279)
Has Child 17 Years or Younger, $t-2$	1.099**	1.093	1.146***
	(0.0411)	(0.0674)	(0.0579)
Whether 16+ Years of Education, $t-2$	0.518***	1.513***	0.412***
	(0.0244)	(0.231)	(0.0280)
Black	0.626***	0.847	0.397***
	(0.0587)	(0.630)	(0.0568)
White	0.572***	0.265***	0.347***
	(0.0481)	(0.0772)	(0.0445)
Region, Northeast, $t-2$	0.707***	1.521	0.758***
	(0.0459)	(0.456)	(0.0721)
Region, North Central, $t-2$	0.720***	0.945	0.672***
	(0.0382)	(0.221)	(0.0529)
Region, West, $t-2$	0.702***	1.042	0.624***
	(0.0418)	(0.276)	(0.0543)
Constant	4.153***		18.75***
	(0.648)		(4.236)
Observations	26,904	16,889	26,904
Number of unique individuals		3,023	6,368

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios. Models (1) and (2) include clustering at the individual level.

Table B15: Impact of Breadwinner Status on Change in Binge Drinking, Men

	Continued Binging	Started Binging	Stopped Binging
VARIABLES	(1)	(2)	(3)
Δ Log Family Income	0.995	1.103	1.03
	(0.0327)	(0.0684)	(0.0414)
Δ Unemployment Status			
Became Unemployed	0.937	1.171	0.875
	(0.161)	(0.265)	(0.176)
Δ Breadwinner Status			
Lost	1.301**	1.19	1.262*
	(0.138)	(0.188)	(0.156)
Gained	0.864	1.212	1.013
	(0.101)	(0.186)	(0.133)
Δ Unemployment $\times$ Δ Breadwinner			
Became Unemployed $\times$ Lost	1.013	1.096	0.995
	(0.402)	(0.579)	(0.464)
Became Unemployed $\times$ Gained	0.513	1.145	0.831
	(0.33)	(0.779)	(0.565)
Age, $t-2$	0.920***	0.904***	0.905***
	-(0.00575)	-(0.00612)	-(0.00582)
Has Child 17 or Younger, $t-2$	1.152**	1.085	1.098
	(0.0748)	(0.0927)	(0.0789)
Whether 16+ Years of Education, $t-2$	0.248***	0.208***	0.318***
	(0.0247)	(0.0249)	(0.0333)
Black	0.307***	0.359***	0.460***
	(0.0691)	(0.0914)	(0.111)
White	0.330***	0.316***	0.486***
	(0.066)	(0.0718)	(0.104)
Region, Northeast, $t-2$	0.861	1.021	1.255
	(0.127)	(0.174)	(0.194)
Region, North Central, $t-2$	0.583***	0.678***	0.816
	(0.0713)	(0.0954)	(0.105)
Region, West, $t-2$	0.523***	0.604***	0.703**
	(0.0705)	(0.0941)	(0.0996)
Constant	4262.5***	4262.5***	4262.5***
	(2830.600)	(2830.600)	(2830.600)
Observations	17,234	17,234	17,234

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. This table reports odds ratios for the likelihood that an individual would maintain his status as a regular binge drinker between years $t-2$ and t ("Continued Binging"), begin binge drinking during this period ("Started Binging"), or stop binge drinking during this period ("Stopped Binging"), relative to the odds that he would begin and end the period as a non-binge-drinker.

Table B16: Impact of Breadwinner Status on Prevalence of Serious Mental Illness and "Good" Subjective Health Rating, Women

	Serious Mental Illness		"Good" Subjective Health	
	(1)	(2)	(3)	(4)
VARIABLES	Logit	Fixed Effects	Logit	Fixed Effects
Log Family Income, $t-1$	0.892***	1.003	1.110***	1.006
	(0.0145)	(0.0328)	(0.00912)	(0.0157)
Unemployed, $t-1$	0.658	0.629	0.635**	0.785
	(0.393)	(0.436)	(0.117)	(0.214)
Not Breadwinner, $t-1$	1.451**	0.955	0.695***	0.757***
	(0.229)	(0.256)	(0.0471)	(0.0779)
Unemployed × Not Breadwinner, $t-1$	1.499	1.304	1.377	1.637*
	(0.961)	(0.993)	(0.284)	(0.489)
Age, $t-2$	1.002	1.020	0.972***	0.900***
	(0.00692)	(0.0219)	(0.00291)	(0.00746)
Has Child 17 Years or Younger, $t-2$	1.234	1.279	1.018	0.918
	(0.201)	(0.342)	(0.0668)	(0.0983)
Whether 16+ Years of Education, $t-2$	0.314***	0.543	2.127***	1.327
	(0.0699)	(0.352)	(0.184)	(0.292)
Black	0.879	0.971	1.096	0.203**
	(0.277)	(1.844)	(0.144)	(0.148)
White	0.981	0.885	1.830***	0.407***
	(0.282)	(0.601)	(0.215)	(0.131)
Region, Northeast, $t-2$	0.992	1.456	1.153	0.280**
	(0.227)	(2.237)	(0.134)	(0.175)
Region, North Central, $t-2$	1.008	1.661	1.109	1.143
	(0.180)	(1.724)	(0.0996)	(0.510)
Region, West, $t-2$	0.775	0.921	0.992	0.831
	(0.174)	(0.998)	(0.0952)	(0.390)
Constant	0.0820***		5.524***	
	(0.0435)		(1.234)	
Observations	13,623	930	26,232	5,973
Number of unique individuals		208		1,081

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios.

Table B17: Impact of Breadwinner Status on Whether Health Better or Worse Than Two Years Ago, Women

	Better	Worse
VARIABLES	(1)	(2)
Δ Log Family Income	1.019	0.991
	(0.0341)	(0.0318)
Δ Unemployment Status		
Became Unemployed	1.09	0.983
	(0.166)	(0.176)
Δ Breadwinner Status		
Lost	1.311**	1.02
	(0.16)	(0.155)
Gained	0.971	0.801*
	(0.101)	(0.0973)
Δ Unemployment × Δ Breadwinner		
Became Unemployed × Lost	0.822	0.254
	(0.439)	(0.275)
Became Unemployed × Gained	0.399	0.242
	(0.277)	(0.263)
Age, $t-2$	0.986***	1.023***
	-(0.00297)	-(0.00347)
Has Child 17 or Younger, $t-2$	0.887*	0.965
	(0.0542)	(0.0673)
Whether 16+ Years of Education, $t-2$	0.991	0.724***
	(0.0658)	(0.0539)
Black	1.286*	0.872
	(0.195)	(0.147)
White	0.952	0.969
	(0.129)	(0.142)
Region, Northeast, $t-2$	0.869	0.829
	(0.0911)	(0.0945)
Region, North Central, $t-2$	0.979	0.93
	(0.0834)	(0.0869)
Region, West, $t-2$	1.229**	1.16
	(0.114)	(0.118)
Constant	4.890***	4.890***
	(0.544)	(0.544)
Observations	16,466	16,466

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios.

Table B18: Impact of Breadwinner Status on Prevalence of Hypertension and Obesity, Women

	Hypertension		Obesity	
	(1)	(2)	(3)	(4)
VARIABLES	Logit	Fixed Effects	Logit	Fixed Effects
Log Family Income, $t-1$	0.954***	1.007	0.951***	1.021
	(0.00848)	(0.0170)	(0.00767)	(0.0157)
Unemployed, $t-1$	1.374*	1.353	0.931	0.585*
	(0.224)	(0.429)	(0.130)	(0.169)
Not Breadwinner, $t-1$	1.091	1.043	0.869***	0.910
	(0.0644)	(0.110)	(0.0438)	(0.0805)
Unemployed $\times$ Not Breadwinner, $t-1$	0.741*	0.731	1.238	1.396
	(0.132)	(0.256)	(0.189)	(0.434)
Age, $t-2$	1.072***	1.235***	1.006**	1.072***
	(0.00325)	(0.0110)	(0.00233)	(0.00738)
Has Child 17 Years or Younger, $t-2$	0.954	0.809**	1.074	1.006
	(0.0573)	(0.0860)	(0.0529)	(0.0881)
Whether 16+ Years of Education, $t-2$	0.716***	1.209	0.556***	1.304
	(0.0518)	(0.262)	(0.0345)	(0.229)
Black	2.571***	10.98***	1.833***	0.754
	(0.362)	(9.558)	(0.213)	(0.476)
White	1.001	1.337	0.841*	0.767
	(0.131)	(0.482)	(0.0879)	(0.212)
Region, Northeast, $t-2$	0.667***	1.573	0.840*	0.652
	(0.0719)	(0.751)	(0.0770)	(0.315)
Region, North Central, $t-2$	0.808**	0.645	0.991	0.841
	(0.0675)	(0.334)	(0.0707)	(0.371)
Region, West, $t-2$	0.779***	0.840	0.911	1.305
	(0.0739)	(0.398)	(0.0718)	(0.555)
Constant	0.0201***		0.709*	
	(0.00475)		(0.132)	
Observations	26,204	6,487	26,280	7,498
Number of unique individuals		1,112		1,312

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios.

Table B19: Impact of Breadwinner Status on Prevalence of Binge Drinking, Women

	Binge Drinking	
	(1)	(2)
VARIABLES	Logit	Fixed Effects
Log Family Income, $t-1$	0.920***	0.965***
	(0.00800)	(0.0121)
Unemployed, $t-1$	0.934	0.745
	(0.127)	(0.152)
Not Breadwinner, $t-1$	1.083*	0.953
	(0.0454)	(0.0623)
Unemployed $\times$ Not Breadwinner, $t-1$	0.997	1.147
	(0.148)	(0.258)
Age, $t-2$	1.001	0.826***
	(0.00192)	(0.00466)
Has Child 17 Years or Younger, $t-2$	1.181***	1.025
	(0.0470)	(0.0693)
Whether 16+ Years of Education, $t-2$	0.487***	1.287*
	(0.0224)	(0.178)
Black	0.602***	0.557
	(0.0662)	(0.393)
White	0.390***	0.338***
	(0.0383)	(0.102)
Region, Northeast, $t-2$	0.633***	1.194
	(0.0425)	(0.374)
Region, North Central, $t-2$	0.776***	0.775
	(0.0441)	(0.203)
Region, West, $t-2$	0.746***	0.838
	(0.0476)	(0.229)
Constant	7.971***	
	(1.372)	
Observations	26,280	15,228
Number of unique individuals		2,758

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Results are reported as odds ratios.

Table B20: Impact of Breadwinner Status on Change in Binge Drinking, Women

VARIABLES	Continued Binging (1)	Started Binging (2)	Stopped Binging (3)
Δ Log Family Income	0.965	1.085	1.001
	(0.0322)	(0.0633)	(0.0402)
Δ Unemployment Status			
Became Unemployed	1.094	1.168	1.171
	(0.192)	(0.268)	(0.233)
Δ Breadwinner Status			
Lost	0.807	1.233	0.866
	(0.112)	(0.212)	(0.139)
Gained	1.347***	1.117	1.341**
	(0.145)	(0.173)	(0.167)
Δ Unemployment × Δ Breadwinner			
Became Unemployed × Lost	1.286	2.04	3.380*
	(0.905)	(1.611)	(2.382)
Became Unemployed × Gained	0.653	0.482	0.715
	(0.41)	(0.449)	(0.501)
Age, $t-2$	0.908***	0.884***	0.891***
	-(0.00588)	-(0.00613)	-(0.00594)
Has Child 17 or Younger, $t-2$	1.172**	0.974	1.091
	(0.0846)	(0.0871)	(0.0866)
Whether 16+ Years of Education, $t-2$	0.162***	0.231***	0.233***
	(0.017)	(0.0271)	(0.0256)
Black	0.376***	0.468***	0.548**
	(0.0939)	(0.13)	(0.146)
White	0.204***	0.265***	0.384***
	(0.045)	(0.0653)	(0.0911)
Region, Northeast, $t-2$	0.582***	0.941	1.057
	(0.0937)	(0.168)	(0.177)
Region, North Central, $t-2$	0.614***	0.777*	0.803
	(0.0818)	(0.116)	(0.112)
Region, West, $t-2$	0.471***	0.505***	0.550***
	(0.0694)	(0.084)	(0.0855)
Constant	19495.3***	19495.3***	19495.3***
	(15326.200)	(15326.200)	(15326.200)
Observations	16,475	16,475	16,475

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. This table reports odds ratios for the likelihood that a woman would maintain her status as a regular binge drinker between years $t-2$ and t ("Continued Binging"), begin binge drinking during this period ("Started Binging"), or stop binge drinking during this period ("Stopped Binging"), relative to the odds that she would begin and end the period as a non-binge-drinker.